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CREATIVE INDUSTRIES AND THE INNOVATIVE URBAN MILIEU: THE CASE OF THE METROPOLITAN CITY OF ROME

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Abstract

Purpose. *In large cities creative industries tend to geographically concentrate. The purpose of this paper is to empirically test the hypothesis that this geographic concentration derives from the benefits on the innovative urban milieu.*
Design/methodology/approach. *A spatial regression model is estimated using as dependent variable the number of creative firms per census block in the Metropolitan city of Rome. Empirical results show that the estimated coefficient of the spatially lagged dependent variable is significantly positive, indicating that the number of creative firms in a census block is influenced by the number of creative firms in neighboring blocks. This enables to explore the conditions accounting for the concentration of creative industries.*
Practical and Social implications. *This paper suggests that knowledge externalities influencing the creative firm's spatial distribution can be interpreted, in an urban scale, in terms of local spatial spillovers, which take the form of spatial dependence. The empirical analysis revealed the existence of a spontaneous creative geography within the metropolitan city of Rome, which is important to further analyse and interpret, if we want to look at the creative clustering from a policy perspective. Creative clusters represent a good opportunity for local governments to catch up with innovation and entrepreneurship policies therefore they need evidence about the existence and the potential role of creative clusters, if they are to encouraging creative industrial growth in particular places.*
Originality of the study. *The paper aims to fill the gap between the regional and the urban scale of analysis in empirical studies on creative industries.*

1. Introduction

Creativity is considered a key competitiveness driver in the knowledge-based economy. Creative industries account for substantial shares of income and employment in developed countries and contribute to increasing the local levels of urban quality and social well-being. The term refers to a range of economic activities that serve consumer demands for entertainment, information, ornamentation and social display (Caves 2000; Hesmondhalgh 2007).

One key characteristic of the creative economy is the extent to which it is an urban, and a global city, phenomenon; the creative energies of this field are powered by the production system of the urban environment, since creativity and its specific forms of expression are part of the complex socio-spatial relationships and rooted in the economic activities, employment, and local labour market dynamics of the city. This stands particularly true for major metropolitan areas like New York, Los Angeles, London, Paris, Milan, Tokyo, where the incidence of employment in the cultural economy is particularly high.

The superiority of dense and diversified urban areas in the transfer of knowledge and innovation output has clearly emerged in research (Henderson et al., 1995; Feldman and Audretsch, 1999; Duranton and Puga, 2001; Audretsch, 2002; Andersson et al., 2005; Berg and Hassink 2014; Durey 2021). It has been widely argued that proximity to knowledge externalities explains the presence of creative industries in urban areas (Mommaas 2004; Cooke and Lazzeretti 2008; Storper and Scott 2009; Branzanti 2015; Chapain and Sagot-Duvauroux 2021). Creative activities embedded in the urban structure sustain cross-fertilization between different activities (Lorenzen and Frederiksen 2008), co-presence of related variety (Boschma and Iammarino 2009), buzz (Bathelt et al. 2004; Storper and Venables 2004; Martin et al., 2015), access to collective learning and shared knowledge resources (Nachum and Keeble 2003).

Conceptually these topics are related to the idea of innovative milieu (Aydalot 1986; Maillat and Crevoisier 1991) characteristic of specific metropolitan areas (Gutierres-Posada et al., 2023). An innovative milieu is defined as "*the set of relationships that occur within a given geographical area that bring unity to a production system, economic actors, and an industrial culture, that generate a localized dynamic process of collective learning and that acts as an uncertainty-reducing mechanism in the innovation process*" (Camagni, 1995).

Creative clusters as a form of economic organization are weakly theorized if compared to industrial clusters (Darchen and Tremblay 2015). The difficulty of analysing creative clustering is related to the lack of a clear definition of what creativity represents in economic terms, which may lead to confusing evidence about its effects on the performance of areas. The territorial scale of investigation represents a further shortcoming; since cluster analysis is rooted in regional studies, urban clusters represent an isolated research field.

We support the thesis that knowledge externalities influencing the creative firm's location decisions can be interpreted, at urban scale, in terms of significance and magnitude of local spatial spillovers (LeSage 2014). We first look at the clustering phenomenon of creative industries within a city, analysing the number of creative firms by census block estimated with a spatially lagged dependent variable. The positive coefficient of the spatially lagged dependent variable supports the existence of creative clusters. Further on, we look at the determinants of the spatial concentration of creative industries in specific areas within the city. After controlling for the spatially autocorrelated error, the empirical results indicate that the creative activities benefit from the advanced urban production system and services. In other words, they benefit from the innovative urban milieu.

The main contribution of this paper is of a methodological nature. We look at the relationships between localization patterns of the creative sector and its 'spatial container' at a very detailed spatial scale, using an original dataset that refers to the Metropolitan City of Rome at the first decade of the 21st century. We are aware that the results, although not representing an updated state of the art, provide valid analyses of the behaviour of creative industries in urban environment.

The rest of the paper is organized as follows. Section 2 provides a literature review on creative clusters. Section 3 describes the study area, the data, and presents some exploratory spatial analysis on creative industries in the Metropolitan City of Rome. Section 4 specifies the econometric model and discusses the identification strategies. This section also presents the estimated results. Section 5 summarizes the main findings and conclusions.

2. Literature review

Interest towards the creative industries is a direct response to new economic paradigms that have accompanied the shift since the late 1970s towards a post-industrial, knowledge-based, global economy. The privileged position of metropolitan areas in the knowledge economy lays in their superiority in transferring knowledge and innovation outputs (Duranton and Puga 2001; Asheim and Parrilli 2012).

Relationships between city and the innovative milieu are analysed in a conceptual perspective by Camagni (1999), who identifies two distinct forms of interaction: i) cities operating as innovative milieu, and ii) innovative urban milieu, consisting of well-defined areas located inside the city, intrinsically exploiting the urban atmosphere. In both cases proximity is crucial, if we consider that close interaction and cooperation amongst firms as well as externalities associated with specialized labour markets are factors that enhance the competitiveness of the local production systems. The latest are often made up of small businesses, which find the necessary externalities in terms of infrastructure and services offered by the urban environment.

Whereas city is the natural place for the development of creative industries, it goes without saying that understanding the characteristics and the functioning of innovative urban milieu is of crucial importance in the study of the creative sector. it is clear, even though simple descriptive statistics, that the recent rapid proliferation of creative firms occur mostly in large and dense urban areas, while many consolidated metropolitan areas have fully developed 'marshallian' creative clusters (Scott, 2010).

The tendency of creative industries to cluster in metropolitan areas, widely illustrated in scientific literature is explained by the benefits derived from localization/specialization economies (Mommaas, 2004; Cooke and Lazzeretti, 2008; De Propris et al., 2009; Boix et al., 2012) and, in more 'inclusive' terms, by the existence of the innovative milieu, characteristic of specific urban/metropolitan areas. Creative industries consist of services that share a symbolic knowledge base and rely upon talent and elevated skills. It is the symbolic knowledge base, related to the creation of contents and aesthetic attributes of products, the specific reason for spatial concentration of creative industries (O'Connor 2004; Scott 2010). Indeed, as symbolic knowledge is highly context-specific and sensitive to distance decay, creative industries tend to cluster in certain districts of the metropolitan areas (Anderson et al. 2005; Boix et al. 2015).

Conventional interpretation of industrial clustering, that is to say localisation and urbanisation economies, can be considered only partial explanation about why creative industries cluster (Wenting et al. 2011). Beneficial externalities brought by specialisation and diversity - the so-called "related variety of activities" (Boschma and Iammarino 2009), the urban assets (Van Oort et al. 2003) and the human capital (Florida 2005), all are to be counted amongst the determinants for creative clustering (Boix et al. 2012; Lazzeretti et al. 2014).

Creative clusters are not easy to frame for two reasons: first, economic activities falling under the umbrella of creative industries are highly differentiated; second, the concept of cluster appears to be fuzzy and chaotic (Martin and Sunley 2003), probably due to the fact that 'cluster is a spatial concept in which a-spatial processes play a prominent role' (Boschma and Klosterman 2005). Difficulties in coping with the functional and geographical complexity of creative clusters are clearly reflected in empirical literature, where this topic is addressed through different methodologies, at different scales and using different notions of clusters (Boix et al. 2015).

Still, the 'creative cluster' approach has proven fashionable enough to produce an increasing number of empirical case studies. These studies examine processes by which creative clusters generate externalities and their relationships with the territory. For example, Lorenzen et al. (2008) show that creative economy is characterized by a tendency to agglomerate in specific places where inter-sector knowledge spillovers are likely to occur. De Propris et al. (2009) argue that creative industries tend to locate near each other depending on their technological complementarities. O'Connor (2004), explains how tacit knowledge - as opposed to codified knowledge - is tied to place, and why creative industries heavily rely on learning-by-doing practices and on skills diffused through specific related networks. Lee et al. (2004) show how open and creative urban environments favour a dynamic entrepreneurship climate. De Jong et al. (2007) investigate the relationship between firm entry rates and concentration of creative industries, showing that areas with higher concentration levels have larger firm entry rates. Similar conclusions obtain Coll-Martinez and Arauzo-Carod (2015) while analysing the location decisions of creative firms in Portugal.

The regional-scale hallmark appears difficult to overcome in terms of econometric modelling, although there is full awareness about regional level of analysis being too coarse to provide appropriate description of creative clusters. Data used in empirical analysis are generally aggregated at the administrative units. Location quotients (LQs) are most often used to analyse regional levels of specialization, considering the creative sector as a whole (Lazzeretti et al. 2008; Boix et al. 2012), or specific sub-sectors (Florida et al. 2010; Campbell-Kelly et al. 2010; Bertacchini and Borrione 2013). As Martin and Sunley (2003) point out, these approaches may suggest cluster's possible locations, but they cannot provide information on their spatial extension.

Whereas it is the very existence of the city that determines creative clustering, it is important to investigate the extent, the characteristics and the intensity of relationships that creative activities establish with the urban context. This observation draws attention towards an important issue in the study of the distribution patterns of the creative industries, revealing that there is an imbalance between the regional and the urban level of analysis that constitutes a gap in the creative industries literature.

Spatial dependence is important when clustering mechanisms are studied at the urban level, because it may be symptomatic of local spatial spillovers: creative firms may locate in particular neighbourhoods where they can benefit from specific characteristics of nearby areas. Spatial spillovers are reflected in spatial autocorrelation, which occurs when the observations of a variable at a particular area are partially correlated with the variables of neighbouring locations (LeSage 2014; Halleck Vega and Elhorst 2015).

In recent years different empirical studies have dealt with spatial econometric techniques applied to the distribution of economic activities at regional or national scale. Some examples are represented by De Dominicis et al. (2013) who analysed the sectorial spatial distribution of economic activities in Italy, Barrios et al. (2009) and their comparative study of Belgium, Ireland and Portugal, Basile (2008) who analysed polarization patterns in the EU, Cruz and Textera (2023), who analysed the determinants of spatial location of creative industries start-ups in Portugal.

When analysing a 'typically' urban phenomenon such as the creative clustering, spatial econometric studies might require the use of data aggregated in small spatial units, such as the census blocks. The absence of empirical applications at this scale is probably due to the fact that variables commonly used to explain the economic significance of creative clustering might be difficult to collect, meaningless, or non-existent at the micro level. The complexity of spatial econometric approaches is another aspect to account for. In this context a common problem is the presence of unobserved variables that may give rise to spatial error correlation. The selected spatial regression model should overcome these problems and ensure valid estimates of spillover effects and valid inferences on their statistical significance (LeSage 2014).

From a methodological point of view interesting suggestions may arrive from studies in socioeconomic, planning and health sciences that make use of small-scale spatial data for exploring local contexts. Typically, variables are count data and the spatial lag econometric model also includes a spatial error term. Estimation and inference of such models is based on econometric methods such as the maximum likelihood or the generalized method of moments (Kelejian and Prucha 1999; 2010).

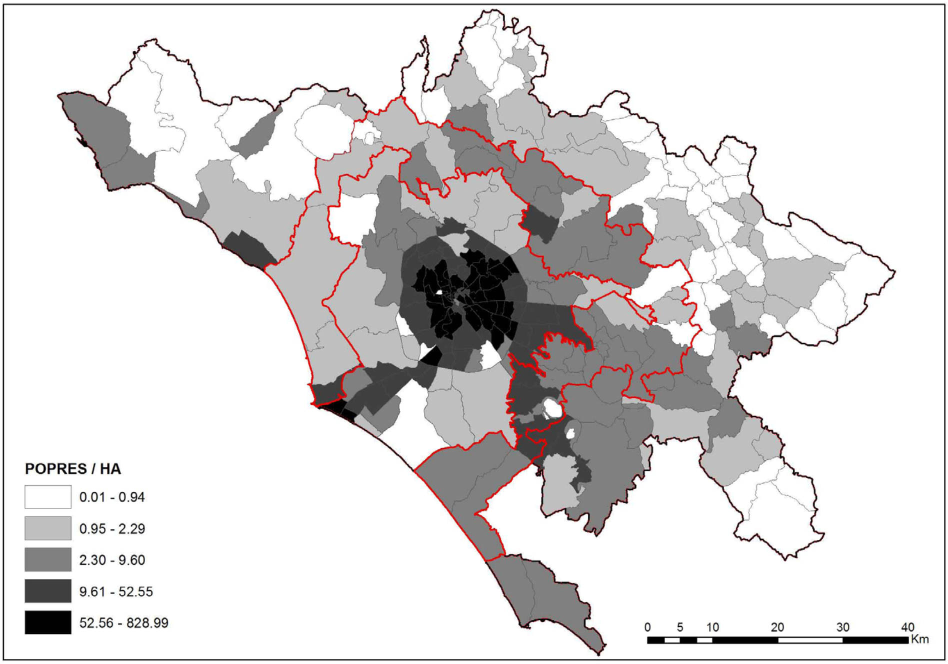
Looking at the micro-geographies of creative industries in the Metropolitan City of Rome, this paper analyses the number of creative industries at the level of census block as a function of context variables through a spatial econometric model. The purpose is to empirically test the hypothesis that the geographic concentration of creative industries derives from the benefits of the innovative urban milieu, which it can be seen as the combination of economic actors, social actors, urban amenities and quality, able to produce an urban ecosystem attractive to the creative industries. The attempt is to take advantage of the vast amount of spatial data available at census block level, as well as of spatial econometrics methods that can grasp the spatial complexity of the urban environment and mitigate the effect of the sharp transitions, which are typical of data aggregations at this spatial level.

3. Creative clusters in the Metropolitan City of Rome

The Metropolitan City of Rome is composed of 121 municipalities covering an area of 5352 km2. According to the last census, 3.997.465 inhabitants live there, accounting for almost 7% of the Italian population. The area is distinguished by the presence of a strongly monocentric urban system: 65% of population live in the municipality of Rome, 25% in first belt municipalities and 10% in peripheral ones (Figure 1).

The Metropolitan City of Rome represents a relevant national creative hub. The incidence of the creative sector value added in the local economy was 7.6% in 2014, slightly higher if compared to Milano (7.0%). Notwithstanding the recent economic crisis, the performance of the creative sector in the study area has remained positive (Symbolia 2015).

Figure 1. Population density in the Metropolitan City of Rome. Read lines depict first belt municipalities.



Source: Population and Housing Census, 2011

3.1. *Definition of the creative sector*

The applied definition is from 'Report on the creative industries' by DCMS (De Propris et al. 2009) adapted for the Italian classification. According to this definition, activities are classified in 'layers', to be interpreted as stages in a creative value chain. Only 'core' creative industries are analysed, consisting of intrinsically creative activities and activities that directly support them in the supply chain.

3.2. *Data*

The principal data source is The Statistical Archive of Local Units of Active Enterprises (ASIA-UL), a business register held by the Italian National Institute of Statistics (ISTAT). Data refer to the creative firms in the Metropolitan City of Rome in the period 2007-2009 and include firm's geographical coordinates, economic activity (5-digit ATECO code) and number of employees[1]. A major drawback is the absence of information on firm demography; thus, data only represent the stock of enterprises in each reference year. Other spatial data are obtained from the Census Bureau, the Revenue Office, or are produced in a GIS system (Table 2).

Data from ASIA-UL show that, in year 2009 the Metropolitan city of Rome counted 32.958 core creative firms out of 342.296: about 10% of share in the local production system. The presence of micro firms is one distinguishing feature: 81,14% are single employee firms, 17,26% have from 2 to 20 employees, 0.86% have from 21 to 50 employees and 0,74% have more than 50 employees.

3.3. *Spatial pattern of creative industries: exploratory analysis*

Data on creative industries are aggregated at the census block, which represent the smallest territorial unit for which population data are available. Creative industries are to be counted in 45% of the census blocks.

Spatial concentration of economic activities may or may not support spatial interdependence. The presence of spatial interdependence is manifested by spatial concentration of similar values (in the case of positive spatial autocorrelation) or of different values (in the case of negative spatial autocorrelation).

The measure used to evaluate the spatial interdependence of the number of creative industries by census block is LISA statistic (Anselin 1995),

[1] The ASIA dataset was provided from ISTAT following an agreement with the University Roma Tre which does not provide for the updating of data in subsequent years. Its use is to be intended as a methodological contribution to the comprehension of the locational dynamics of CCIs in urban environment.

which is a local version of Morans'*I* (Moran 1950). LISA statistic returns a measure of spatial autocorrelation for each individual location and provides information about which unit values are statistically significant compared to spatial randomness. LISA statistic for each observation i is given by the following expression:

$$I_i = \frac{X_i - \bar{X}}{m_0} \sum_j W_{ij}(X_j - \bar{X}), \quad \text{with} \quad m_0 = \frac{1}{n} \sum_i (X_i - \bar{X})^2 \qquad , (1)$$

Where: x_i is the studied variable in region *i*, is the average sample value, *n* is the sample dimension, W_{ij} are binary spatial weights: value 1 is given to 1st order neighbours, and 0 to all the other spatial units. The summation over *j* is such that only neighbouring values of *j* are included.

The strength of spatial autocorrelation is analysed through the Moran scatterplot, which determines the extent of linear association between the number of creative industries in a given location and in neighbouring locations. The spatially lagged transformation of the variable (y-axis) is regressed on the original standardized variable (x-axis). The slope of the Moran's *I* represents the autocorrelation coefficient: the steeper the slope is, the stronger is the global autocorrelation. The four quadrants of the scatter plot describe an observation's value in relation to its neighbours: high-high, low-low (positive spatial autocorrelation) and high-low, low-high (negative spatial autocorrelation). Inference is based on the conditional permutation approach. The value x_i at location *i* is held fixed, while the remaining values are randomly permuted over all locations. The *p-valu*es obtained for the LISA statistics are then pseudo significance levels.

Table 1 shows, in the second column, the distribution of the number of census blocks in the quadrants of the Moran scatterplot and in the third column the census blocks having a significant *p-value*. It is interesting to observe that the percentage of those with significant p-value is much higher for spatial units lying in the high-high quadrant, indicating that spatial clustering of high values ('hot spots') may occur in different areas.

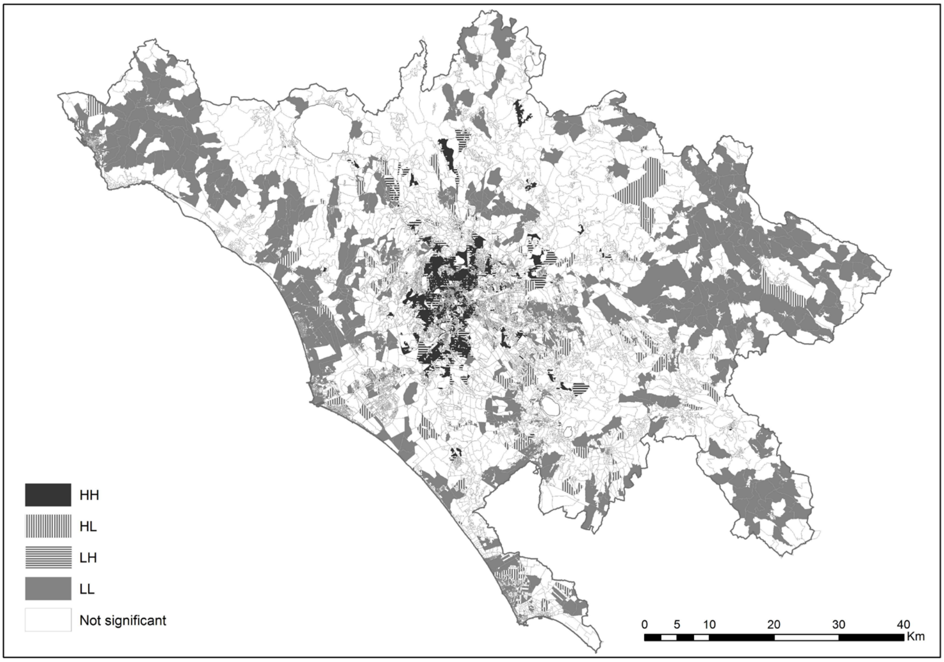
Table 1. LISA statistics and the significance levels.

Moran Scatter Plot Quadrant	Total	Significant	% Significant	Significance levels			
				0.001	0.01	0.05	NS
HH	4087	2496	61.07	52.90	31.42	23.43	13.17
HL	1604	341	21.26	7.15	3.14	4.66	10.45
LH	3674	1504	40.94	20.74	18.63	21.01	17.96
LL	10270	3213	31.29	19.21	46.81	50.90	58.41
Total spatial units	19635	7554	38.47	100.00	100.00	100.00	100.00

If we take a closer look at the significance levels (columns 5 to 8 in Table 1), we observe that census units having a positive relationship of high values represent almost 53% of the total units with *p-values* significant at p = 0.001. Conversely, the share of census units of this type represents 13 % of the total non-significant units. The opposite holds for units having a positive relationship of low values. They have a share of 58% of the total non-significant units, of 51% total units with p-values significant at p = 0.05 (weakly significant) and of 19% of the total units with p-values significant at p = 0.001. These results further support the assumption of the spatial clustering of creative firms in the study area.

It is possible to map the location and shape of clusters. Figure 2 shows census blocks with a significant Local Moran statistic classified by type of spatial correlation: the high-high and low-low locations suggest clustering of similar values, whereas the high-low and low-high locations indicate spatial outliers. As it can be observed from the map, spatial clustering of high values ('hot spots') occurs in different areas of the consolidated city. The phenomenon is particularly intense in the neighbourhoods just north to the historic centre. Consistent hot spots are also observed in the western neighbourhoods and in the southern neighbourhoods. It is significant the quasi absence of creative clusters in the eastern sector of the consolidated city, traditionally industrial, which hosts some of the poorest and infamous neighbourhoods of Rome.

Figure 2. *LISA cluster map for creative firms in the census blocks in the Metropolitan City of Rome, 2009.*



To further investigate the conditions that account for the spatial clustering of creative firms, an econometric model is defined and illustrated in the following section.

4. Empirical analysis

The observed spatial dependence of the number of creative firms per census block reveals the tendency or creative industries to concentrate in specific places where, most likely, they can benefit from the innovative urban milieu acting as a catalyst for the creation of symbolic knowledge. In this context spatial dependence is considered symptomatic of the existence of local spatial spillovers, which can be formally defined. While considering local spillovers in estimating the spatial econometric model, we do not consider the potential adjustments produced in all the regions by changes taking place in one region, meaning that we do not consider endogenous interaction and feedback effects (LeSage 2014).

The spatial structure is incorporated in the regression model in the form of a spatial weight matrix, defined exogenously by the census blocks polygons, which represent an arbitrary, instrumental delimitation of the spatial units.

4.1. *Key variables*

Creative clustering stem from a combination of interrelated factors, which refer to a physical dimension, an economic dimension and a social dimension. The assumption is that the explanatory variables, observed in the years prior to the year of reference, may have influenced location choices of creative firms.

The dependent variable is 'Number of creative industries per census block' in the reference year 2009.

The urban production system is approximated by the number of firms operating in high-tech sectors in the period 2007-2009 (average value and difference), and by the number of firms operating in the traditional manufacturing sectors in the same period (average value and difference). These variables account for the density of the economic agents of the territory (Turok 2003).

The physical environment is described by a second group of explanatory variables. Urban quality (architecture and streetscapes) is approximated by the average real estate prices of offices and shops in the period 2006-2009 and by the average real estate prices of housing in the period 2006-2009. The average renting prices of offices in the period 2006-2009 and the average renting prices of houses in the period 2006-2009 are also considered, since affordable renting are a possible driver for locational choices of small firms. The presence of buildings used as offices is considered a possible driver of locational choices of large firms.

The access to a wide variety of specialised services and cultural amenities highly influences the location choices of creative industries. These aspects are taken into consideration by counting the number of museums, art galleries, theatres, and entertainment facilities in the census blocks. Considering the monocentric structure of the urban system, Euclidean distance from the city centre is a proxy for an increased accessibility of creative activities to urban specialised services and infrastructures. Other space-specific characteristics are the Euclidean distance from the three main city airports, the Euclidean distance from major accessibility nodes to the national road system, the Euclidean distance from rail and metro stations.

Human capital in dense metropolitan areas embodies many different skills, aptitudes and sensibilities, which are essential for creative clustering. For each census block we count the total resident population, the population holding a bachelor or a diploma as proxy for the presence of skilled labour force and the foreign residents as proxy for cultural diversity. Table 2 presents the summary statistics of variables.

Table 2. Descriptive statistics of variables.

Variable	Measuring unit	Mean	SD	Min	Max	Source
CREATIVE INDUSTRIES	n_o	1.62	3.22	0.00	71.00	ASIA
AVERAGE HT INDUSTRIES (07-09)	n_o	0.52	1.42	0.00	39.33	ASIA
AVERAGE TRADITIONAL MANUFACTURE (07-09)	n_o	0.51	1.41	0.00	53.67	ASIA
DIFF. HT INDUSTRIES (07-09)	n_o	0.01	0.59	-9.00	8.00	ASIA
DIFF. TRADITIONAL MANUFACTURE (07-09)	n_o	0.03	0.55	-6.00	14.00	ASIA
AVERAGE HOUSING PRICE (06-09)	€/m^2	3119.91	1632.25	0.00	10375.00	OMI
AVERAGE OFFICES PRICE (06-09)	€/m^2	2956.55	2142.92	0.00	11618.80	OMI
AVERAGE HOUSING RENT (06-09)	€/m^2 x month	12.28	7.67	0.00	42.19	OMI
AVERAGE OFFICES RENT (06-09)	€/m^2 x month	12.26	9.64	0.00	46.91	OMI
OFFICE BUILDINGS	n_o	0.74	2.56	0.00	139.00	CENS
CULTURAL FACILITIES	n_o	0.02	1.04	0.00	14.00	ASIA
DISTANCE FROM THE CITY CENTRE	meters	17312.40	14872.30	50.00	66234.90	GIS
DISTANCE FROM AIRPORTS	meters	13054.60	11196.90	180.28	58829.40	GIS
ROAD ACCESSIBILITY	meters	6383.23	7449.16	50.00	40432.20	GIS
RAIL ACCESSIBILITY	meters	2324.81	2749.18	50.00	25323.90	GIS
RESIDENT POPULATION	n_o	188.46	243.24	0.00	2594.00	CENS
RESIDENTS WITH HIGHER EDUCATION	n_o	21.89	35.96	0.00	364.00	CENS
FOREIGN RESIDENTS	n_o	6.59	17.08	0.00	1173.00	CENS

Sources:
ASIA UL: Database on local units of firms, ISTAT (Istituto Nazionale di Statistica); years 2007-2009.
OMI: Database "Osservatorio del Mercato Immobiliare", Agenzia del Territorio; years 2006-2009.
CENS: Population and housing Census 2001, ISTAT (Istituto Nazionale di Statistica).

4.2. Econometric model

We estimate an econometric model that includes a spatially autoregressive lagged dependent variable WN, where W is a $J \times J$ spatial weights matrix, and $N = (N_1, N_2, \cdots, N_J)'$ is a vector of the number of creative firms in the census block. By convention, the diagonal elements of the spatial weights matrix are set to zero and inside each row the elements are transformed in such a way that they sum to one. The effect of the number of creative industries in another census block can be expressed as $\sum_k w_{jk} N_k$, where w_{jk} is the elements of the spatial weights matrix, which does not contain N_j because w_{jj} is defined as zero.

The spatial lag model is defined as follows:

$$N = \rho WN + X\beta + \varepsilon \qquad (2)$$

where ϱ is the autoregressive parameter for the spatial lag term, X is the matrix of geographic attributes, β is the corresponding vector of coefficients and ε is the error vector, assumed to be homoscedastic, independent and identical across the units. A significant estimate of the coefficient of the spatial autoregressive lagged dependent variable *WN* implies that the number of creative firms by census block unit depends on the number of creative firms in the closest neighbour area. If this is not the case, we assume that $\varrho = 0$, so we have a spatially independent model:

$$N = X\beta + \varepsilon \qquad (3)$$

The assumption of homoscedasticity, independency and identical distribution across the observations for ε is violated if there are spatially dependent omitted variables. Alternatively, we can allow different specifications of the error process and spatially lagged variable. In particular, we specify a first order autoregressive error term:

$$\varepsilon = \lambda W\varepsilon + u \qquad (4)$$

where λ is the spatial autoregressive error parameter and u is an uncorrected and homoscedastic error term.

To check for spatial dependence, we define different types of spatial weights matrices and test for spatial autocorrelation on the OLS residuals using Moran's *I* statistics. We adapt the model to our data as follows (Anselin 2006).

1. Estimate the spatially independent model (Equation 3) by means of OLS.
2. Apply the Lagrange multiplier test statistic LM_λ for $H0 : \lambda = 0$ versus $H1 : \lambda \neq 0$ and LM_ϱ for $H_0 : \varrho = 0$ versus $H_1 : \varrho \neq 0$.
3. Apply the Lagrange multiplier test statistic $LM_\lambda{}^*$ for $H_0 : \lambda = 0$ versus $H_1 : \lambda \neq 0$ (with $\varrho \neq 0$) and $LM_\varrho{}^*$ for $H_0 : \varrho = 0$ versus $H_1 : \varrho \neq 0$ (with $\lambda \neq 0$).

If the Lagrange multiplier test statistic LM_λ leads to the rejection of H_0: $\lambda = 0$, then we refer to the spatial error model (4); while if with LM_ϱ the null hypothesis $H_0 : \varrho = 0$ is rejected we use the spatial lag model (2). When both tests in b) give not enough evidence against the null, we adopt Equation (3) as the final specification. If this were the case, it results that the number of creative industries in a block does not depend on the number of creative industries in the closest neighbour area. If both tests in b) reject the null, we carry out the robust LM tests in c). If $LM_\varrho{}^*$ test is significant but $LM_\lambda{}^*$ is not, we estimate Equation (2) using maximum likelihood or spatial two-stage least squares method. If $LM_\lambda{}^*$ is significant but $LM_\varrho{}^*$ is not, we estimate Equation (4) using maximum likelihood (Anselin 1988) or generalized moments method for the autoregressive parameter (Kelejian and Prucha 2010). The last case implies that the creative network effect across the census blocks is zero. If $LM_\lambda{}^*$ and $LM_\varrho{}^*$ are significant we combine (2) and (4) as follows:

$$N = \rho WN + X\beta + \varepsilon,\ \varepsilon = \lambda W\varepsilon + u \quad (5)$$

and estimate the resulting spatial lag model with spatial error term using generalized feasible spatial two-stage least squares (GS2SLS). The model in Equation (5) is based on the estimation theory for the regression parameters by Kelejian and Prucha (2007), which is robust against possible misspecifications of the spatial dependence structure in the model disturbances. The model has consistent spatial heteroskedasticity and autocorrelation (HAC) estimators (Piras 2010). This aspect is of paramount importance if we consider that census blocks reveal highly different in size and characteristics. The spatial lag model with spatial error term has been already applied at the micro-scale urban level by Iwata and Karato (2011) for the purpose of analysing the spatial distribution of homeless people in Osaka City. In their paper, the dependent variable is the number of homeless people per census block and the explanatory variables typically represent the urban *milieu*, including accessibility characteristics, socio-economic characteristics, urban functions and amenities.

As a robustness check for spatial dependence, we use four different types ($t = 1, 2, 3, 4$) of spatial weights matrices:

$$W_t : w_{jk}^t = \begin{cases} \dfrac{d_{jk}^t}{\sum_{j\neq} d_{jk}^t}, & \text{if } j \neq k \\ 0, & \text{if } j = k \end{cases} , (6)$$

where
$d^1_{jk} = 1$ if j and k are 1st order neighbours, and 0 otherwise,
$d^2_{jk} = 1$ if j and k are 2nd order neighbours, and 0 otherwise,
$d^3_{jk} = 1$ if distance between j and $k < 1000$ meters, and 0 otherwise,
$d^4_{jk} = 1$ if distance between j and $k < 2500$ meters, and 0 otherwise.

4.3. *Estimation results*

We first estimate the OLS model in Equation (3), and test for spatial autocorrelation on the OLS residuals using Moran's *I* statistics performed by applying different types of spatial weights matrices, as specified in section 4.2. The Moran's *I* statistics in Table 3 reject the hypothesis of no spatial autocorrelation, regardless of the weights specifications, because the *p*-values of Lagrange multiplier test statistics LM_ϱ and LM_ϱ^* are sufficiently small. These imply that the spatial lag term (ϱ) must be considered. Furthermore, the test statistics LM_λ and LM_λ^*, reject null hypotheses when the autoregressive parameter is zero. Therefore, the spatial lag model with spatial error term in Equation (5) is estimated.

Table 3. Diagnostics test for spatial autocorrelation.

Weights and test	**Value**	***p-value***
W1		
Moran's *I*	16.10910	0.00000
LM (lag)	159.18000	0.00000
LM (error)	255.11680	0.00000
LM* (lag)	6.80310	0.00910
LM* (error)	102.74000	0.00000
W2		
Moran's *I*	22.19620	0.00000
LM (lag)	240.61810	0.00000
LM (error)	481.03770	0.00000
LM* (lag)	12.37720	0.00043
LM* (error)	252.79680	0.00000
W3		
Moran's *I*	18.76990	0.00000
LM (lag)	206.00240	0.00000
LM (error)	342.85490	0.00000
LM* (lag)	12.34410	0.00044
LM* (error)	149.19660	0.00000
W4		
Moran's *I*	20.67030	0.00000
LM (lag)	170.39070	0.00000
LM (error)	403.06680	0.00000
LM* (lag)	15.89230	0.00007
LM* (error)	248.56840	0.00000

Note: Moran's I ~ N [0, 1]. LM ~ X^2 [1].

Table 4 shows in column (a) the estimated results of Equation (3) and in column (b) the estimated results of Equation (5). First order contiguity matrix (W1) was used to estimate the GS2SLS model, since it provided the best fit. W1 can be considered exogenously specified, being composed by arbitrarily delimited spatial units.

The hypothesis that the spatial autoregressive error is not present ($\lambda = 0$) is rejected at the 0.1 per cent significance level. The spatial lag term (ϱ) reflects the spatial dependence inherent in the sample data, measuring the average influence on observations by their neighbouring observations. It has a positive effect, and it is highly significant. Spatial dependence is indicative of the presence of local spatial spillovers, which occur when the observations of a variable at a particular area are partially correlated with the variables of neighbouring locations. This has clear implications for the geographic concentration of creative firms by census unit, indicating that creative firms locate in places where they can benefit from specific characteristics of nearby areas.

The signs of the control variables did not change with respect to the OLS model in column (a). However, while controlling for spatial effects some striking differences are observed in the significance levels of some variables.

The difference of firms in the manufacturing sector appears to be less significant than in the OLS estimation. As expected, creative industry appears to be more related to the presence of firms operating in the high-tech sector. Looking at the size of the coefficient, we can estimate that a 10% increment in the average value of the number of firms operating in the HT sector causes an increment in the average number of creative industries equal to 3.5%.

The average real estate prices for offices and shops become less significant as well, while the number of buildings dedicated exclusively to offices and shops become insignificant. These results seem to validate the hypothesis that creative firms in the Metropolitan region of Rome do not require office space. Conversely, the average housing rents gains significance.

As far as it concerns the size of the coefficients, we can calculate that a 10% increase in the average value of the housing price, which means 312 eur/m^2, accounts for an increase in the average number of creative industries equal to 4%; while a 10% increase in the average value of the office price, causes the average number of creative industries to augment by 1.4%.

It is interesting to notice that cultural and social facilities appear to be considerably less significant than in the OLS estimation. The other substantial difference concerns the number of foreign residents, which become insignificant, showing that cultural diversity is not (yet) a determinant for creative clustering in the study area.

Other variables to be mentioned are the average number educated people, whose increment by 2.12 units (10% of the average number) causes an average increase in the number of creative industries equal to 4.3%, and the average distance from the city centre whose increment by 1.7 km (10% of the average distance) causes an average decrease in the number of creative industries equal to 1.3%.

Column (c) in Table 4 illustrates the estimated results of Equation (5) using as dependent variable the number of single employee creative firms per census block instead of the total number of creative firms. Observed significance levels of the explanatory variables for this subset are very similar to those of the overall dataset illustrated in column (b). This result highlights the fact that the ownership structure of the creative industry in the Metropolitan region of Rome, where self-employed people represent more than 80% of the firms, highly affects the spatial behaviour of the creative sector.

Table 4. Model estimation: a) OLS; b) GS2SLS; c) (GS2SLS) for single employee firms.

	a)		b)		c)	
Variable	**Coef.**	***t*-value**	**Coef.**	***t*-value**	**Coef.**	***t*-value**
(INTERCEPT)	-3.8080E-01***	-6.400	-4.0694E-01***	-5.977	-2.6072E-01***	-4.75
AVERAGE HT INDUSTRIES (07-09)	1.0990E+00***	91.889	1.1025E+00***	23.068	6.8387E-01***	14.685
AVERAGE TRAD. MANUFACTURE (07-09)	1.6120E-01***	12.757	1.6144E-01***	5.134	1.4595E-01***	5.631
DIFF. HT INDUSTRIES (07-09)	2.2430E-01***	11.227	2.2305E-01***	4.568	1.3117E-01**	3.053
DIFF. TRAD. MANUFACTURE (07-09)	-1.6000E-01***	-7.155	-1.5854E-01**	-2.964	-1.4271E-01**	-3.100
AVERAGE HOUSING PRICE (06-09)	2.3800E-04***	9.948	2.1016E-04***	9.674	1.5236E-04***	8.401
AVERAGE OFFICES PRICE (06-09)	8.9800E-05***	3.441	7.8910E-05**	3.047	5.8626E-05**	2.899
AVERAGE HOUSING RENT (06-09)	-1.4520E-02*	-2.165	-1.2546E-02**	-2.781	-9.3842E-03*	-2.460
AVERAGE OFFICES RENT (06-09)	-4.7120E-03	-0.879	-3.6452E-03	-0.846	-4.9461E-03	-1.370
OFFICE BUILDINGS	-1.5630E-02*	-2.430	-1.8007E-02	-0.857	-3.3679E-02	-2.252
CULTURAL FACILITIES	7.3390E-01***	8.439	6.9362E-01*	2.317	4.3261E-01*	2.110
DISTANCE FROM THE CITY CENTRE	-1.4920E-05***	-5.043	-1.1915E-05***	-3.942	-1.0434E-05***	-4.000
DISTANCE FROM AIRPORTS	1.4440E-05***	4.384	1.1911E-05***	3.863	9.2144E-06***	3.448

ROAD ACCESSIBILITY	6.5380E-06**	2.648	6.5200E-06***	4.579	6.1855E-06***	5.184
RAIL ACCESSIBILITY	6.5840E-06	1.078	7.0244E-06 .	1.768	5.3288E-06	1.618
RESIDENT POPULATION	-1.0180E-03***	-11.143	-8.8034E-04***	-4.975	-3.0917E-04*	-2.220
RESIDENTS WITH HIGHER EDUCATION	3.3920E-02***	53.829	3.2037E-02***	18.885	2.8562E-02***	19.423
FOREIGN RESIDENTS	4.7240E-03***	4.934	4.3215E-03	1.359	2.9136E-03	1.128
λ			4.7975E-02**	2.912	6.4576E-02**	3.251
ϱ			1.0650E-01***	4.914	6.6324E-02**	2.660
Adj. R^2	0.5954					
Number of Obs.	19635		19635		19635	

Notes: Dependent variable is the number of creative firms.

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

5. Conclusions

Creative industries represent an important growth and employment sector in advanced post-industrial economies and have played a key role in processes of urban regeneration of many deindustrialised areas. The study of their spatial organisation represents an important challenge, in the light of the fact that scientific literature does not provide sufficient empirical evidence on this research topic. Indeed, there is a gap between the regional and the urban level of analysis, probably due to the fact that location determinants of creative industries are difficult to define in the context of complex and dense urban environments.

This paper suggests that knowledge externalities influencing the creative firm's spatial distribution can be interpreted, in an urban scale, in terms of local spatial spillovers, which take the form of spatial dependence. A spatial autoregressive model with autoregressive disturbances is estimated, that provides significant inputs to understanding the geographic distribution of creative industries and the variables that account for this concentration. The empirical results indicate that creative firms benefit from some specific characteristics of the nearby areas. In the Metropolitan City of Rome creative firms tend to cluster in places where they can take advantage of the skilled labour force, the presence of economic activities operating in the hi-tech sectors, a large number of urban functions and high levels of urban quality. Accessibility to transportation infrastructures and office space availability appear less relevant, probably due to the high incidence of micro firms, whose location most probably coincides with that of the owner's residence.

The high significance of many explanatory variables suggest that the phenomenon of creative clustering can be interpreted in terms of multiple types of externalities relying upon the existence of the innovative urban milieu.

The empirical analysis revealed the existence of a spontaneous creative geography within the metropolitan city of Rome, which is important to further analyse and interpret, if we want to look at the creative clustering from a policy perspective. Creative clusters represent a good opportunity for local governments to catch up with innovation and entrepreneurship policies therefore they need evidence about the existence and the potential role of creative clusters, if they are to encouraging creative industrial growth in particular places. In this context, aspects related to the characteristics of the different creative segments and their co-agglomeration patterns would be important to investigate in the micro-scale, notwithstanding the evident complexity of this topic.

Working at the census block level represents a novelty with respect to previous empirical literature on creative clustering. Nevertheless, there are some considerations to be done about the spatial empirical model used in this study. The first is about the lack of specific models operating at the micro-scale, that adequately account for causality, interaction effects and spatial spillovers. The second concern is that, despite the high disaggregation level, the model is still unable to capture the impact of the distribution of creative activities within the census block. This problem becomes particularly striking in peripheral and less urbanised areas, where census units are larger. To overcome this problem, better explanatory variables are needed, that directly measure spatial distribution effects. We hope to be able to treat these issues in future research. While the model is valid in general, and it can be applied at the urban scale if the detail of the data allows it, the research conducted in the first decade of 2000 in Rome has led to significant results for the understanding of the CCIs phenomenon at an urban level that still have important implications today.

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