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Agglomeration, accessibility and Industrial Location: Evidence from Spanish municipalities

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Abstract

This paper deals with the location decisions of manufacturing firms in Spain. We analyse how agglomeration economies and transport accessibility influence the location decisions of firms at municipality level and in three industries. The main empirical contributions of this paper are the econometric techniques used (spatial econometric models) and some of the explanatory variables (local gross domestic product, road accessibility, and the characteristics of firms in neighbouring municipalities). The results show that agglomeration economies and accessibility are important in industrial location decision-making.

JEL Classification Codes: R10, R12, R15, R30

Key words: agglomeration, accessibility, industrial location, spatial econometrics, Spain

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1. Introduction

The location decisions of new firms are of key importance because local economic growth partially depends on the capacity to attract new manufacturing investments. Here we focus on how the geographical scope and accessibility of agglomeration economies influence firm location decisions at the local level in Spain. This paper contributes to the empirical literature on firm location by focusing on the location decisions of firms using Spatial Statistics and Spatial Econometrics and such other variables as road accessibility, local gross domestic product and the characteristics of neighbouring municipalities. Accordingly, we analyse how the accessibility and characteristics of selected sites and those of their neighbours shape a firm's location decisions.

On the one hand, improvements in accessibility increase the potential interaction between sites (travel time is reduced) and the attractiveness of location. On the other hand, attractiveness can also be explained by the existence of many firms belonging to the same industry (location economies), by the industrial diversity and size of the urban economy (urbanization economies) or, simply, by a "follow the leader's locational decision" strategy. We assume that the location decisions and location processes in one place are related to location decisions and location processes in neighbouring places. Therefore, the locational behaviour of nearby establishments may be spatially autocorrelated, but surprisingly most location studies do not take these spatial autocorrelation issues into consideration, as if activity outside a particular area has no effect on activity within that area. Additionally, most of these studies do not use techniques from Spatial Statistics or Spatial Econometrics, which have been developed to deal with spatial autocorrelation issues.[1] As is widely known in geographical analysis, underlying spatial processes, such as the geographical scope of agglomeration economies, or the inappropriate treatment of sample data with spatial autocorrelation can lead to inefficient and/or biased and inconsistent estimates.[2]

We assume that location patterns can depend on the specific characteristics of manufacturing industries. We tested this assumption in ten manufacturing industries: Food, drinks, and tobacco; Clothes and leather; Wood and furniture; Printing and paper; Chemistry; Other non metallic minerals; First transformation of metals; Machinery; Electric and electronic equipment and Transport equipment.

This paper is organised as follows: Section 2 reviews the literature on industrial location that focuses on the geographical scope of agglomeration economies and accessibility; Section 3 presents an explanatory spatial analysis; Section 4 provides data, econometric specifications and results; and Section 5 concludes.

2. Determinants of the location of manufacturing establishments: accessibility and the geographical scope of agglomeration economies

The determinants of new plant locations have been analysed in many recent papers, most of which focus on the so-called neoclassical location determinants in their attempts to explain such decisions (see Arauzo-Carod et al. 2010 for a detailed review of this empirical literature). This paper fits into this body of literature because it focuses on the role played by agglomeration economies and accessibility, largely because of the acknowledged importance of the former and the fact that the latter has received little

[1] Some exceptions are Alañón et al. (2007) and Autant-Bernard (2006) among others.
[2] See Anselin (1988).

attention from scholars even though it has implications for firms' strategies and public policies.[3]

Some scholars have analysed how improvements to the road infrastructure affect the productivity of the private sector that uses it (García-Milà and García-Montalvo, 2007; García-Milà and McGuire, 1992; Carlino and Mills, 1987; Carlino and Voith, 1992) and how accessibility can have a positive impact on productivity (Rice et al., 2006). It has also been pointed out that the consequences of improved accessibility are industry-specific (Chandra and Thompson, 2000), because different industries have different requirements in terms of transportation of inputs and outputs, which means that proximity to the highway network (henceforth HN) will not be the same for all industries.

Holl (2004b) shows that the construction of the HN in Portugal (1986-1997) has modified the spatial distribution of firm location, since municipalities with improved accessibility to the HN have become more attractive to new firms and there has been a deconcentration of economic activity as peripheral municipalities have increased their accessibility and more new firms have located there. Spain too has provided empirical evidence about the impact of HN on the location decisions of firms (Holl, 2004a and Arauzo-Carod, 2005). The main results agree with those of other countries: municipalities located near the HN have greater locational attractiveness than other municipalities, and this effect depends on the accessibility requirements of each manufacturing industry.

[3] Following Beckman (2000), we consider that travel time is the most appropriate measure of distance between two municipalities, and that the accessibility indicator is the amount of time needed to access the highway network (HN) from each municipality. It is important to take into account that differences in transport infrastructures partially determine travel time, and also that other accessibility measures may produce different results.

Additionally, there is a twofold relationship between accessibility improvements and agglomeration economies. On the one hand, accessibility improvements may cause production to be moved to the periphery and subsequently transported to central makets. This would erode agglomeration economies (Haughwout, 1999). On the other hand, accessibility improvements may enhance the spatial effects of agglomeration economies, since plants that are distant from one another would be able to benefit from the advantages of these agglomerations. Accessibility, then, may enlarge the geographic scope of agglomeration economies, which attenuates the benefits of agglomeration with physical distance, since, *ceteris paribus*, when economic agents are closer there is more potential for interaction.

As stated in the introduction, most scholars have implicitly assumed that activity outside a location has no effect on activity within it (Rosenthal and Strange, 2004). Some, however, have taken into account the geographic scope of agglomeration economies (see, for example, Ciccone and Hall, 1996; Ellison and Glaeser, 1997; Ciccone, 2002 and Rosenthal and Strange, 2003) and shown that spatial lags do exist, although the benefits of agglomeration economies attenuate with distance. Empirical evidence on the geographic scope of agglomeration economies for small areas can be found in Rosenthal and Strange (2001, 2003) for the US zip codes; in Viladecans (2004), Alañón et al (2007), and Jofre-Monseny (2009) for Spanish municipalities; in Duranton and Overmans (2002) for UK postcodes; and in Van Soest et al. (2006), for a Dutch province, also at zip code level. Rosenthal and Strange (2001) found that the effect of agglomeration economies is strongest at closer distances (within one mile and the same industry) and that these effects are still significant within fifteen miles, but only for the same industry. Rosenthal and Strange (2003) show that the geographic scope of localization economies is larger than that of urbanization economies, since they found that employment outside a particular industry has an inconsistent and frequently insignificant effect. Viladecans (2004), who restricts her analysis to Spanish cities with more than 15,000 inhabitants, found that urbanization economies influence location in most industries, while localization economies play a minor role, and the agglomeration effects only spilled over the city borders in three of the six manufacturing industries analyzed. Jofre-Monseny (2009) studied Catalan municipalities and found evidence on the geographical scope of location economies for the Textile and Wood and furniture industries, and of urbanization economies for Medical, precision and optical instruments, Chemical products and Metal products except for Machinery industries. Alañón et al. (2007) studied most mainland Spanish municipalities and their results show that the strongest effect is found at around 20 kilometres. Duranton and Overman (2002) extend geographic localization to less than fifty kilometres and Van Soest et al. (2006) conclude that agglomeration economies may well operate on a geographic scale that is smaller than a city, since they only found evidence for interurban externalities for manufacturing, which is analysed as a single industry.

In any case, agglomeration economies and accessibility are closely linked, mainly thanks to transport infrastructure. In this regard, it should be taken into account that investments in the road network are greater in areas with a greater concentration of economic activity and a greater capacity to attract new firms.[4] It is necessary, therefore, to control the non-observable locational characteristics that influence both the extent of the road network and the location of firms. It is also important to analyse whether the

[4] See Holl (2004a) for a more extensive discussion of this issue. In any case, the endogeneity problem will occur if the transport infrastructure programs are intended to improve connections between the larger urban metropolitan areas. The problem will be smaller if they are intended to improve the accessibility of small municipalities to the road network.

construction of new transport infrastructure is an exogenous variable and thus not related to previous economic growth in this area. In this context, Chandra and Thompson (2000) show that the location decisions for these infrastructures are endogenous for the larger (metropolitan) areas (in fact, construction is motivated by their economic growth and the level of congestion on existing roads), and exogenous for the smaller (non-metropolitan) areas. In particular, Chandra and Thompson (2000) show that income increases in non-metropolitan municipalities that are adjacent to freeways but decreases in non-adjacent municipalities due to activity relocation since companies prefer to locate in areas that are more accessible to this infrastructure.

Nevertheless, the important issue is how to deal with this (potential) endogeneity. In a recent paper in which they analysed the effects of interstate highways on the growth of US metropolitan areas, Duranton and Turner (2010) used instrumental variables (rail and highway infrastructures existent in previous years) to control for this potential bias. This is a reasonable solution because their data is more prone to suffering from the endogeneity problem as they use only metropolitan areas. In a similar approach, Baum-Snow (2007) also uses previous highway infrastructures as instruments to analyse suburbanisation in US metropolitan areas. However, as we have mentioned above, in smaller urban units such as municipalities, the situation changes and endogeneity problems diminish.[5] For example, Melo et al (2010) analyse the impact of transport infrastructure on firm location for Portuguese municipalities. In particular, they consider that (p. 139) "… the use of disaggregated spatial data, in this case, municipal-level data, can reduce endogeneity problems because transport investment decisions are generally determined at bigger levels of government". This opinion is shared by other researchers

[5] We acknowledge that the relationship between improved accessibility and firm location must be analysed with extreme caution, since there may be a problem of endogeneity, even if this issue is not the target of our research.

who use this type of spatially disaggregated data (for example, see Holl 2004A) also for Portuguese municipalities. Additionally, given that both the Portuguese and Spanish highway systems are being funded to quite a considerable extent by the EU, the criteria about this exogenous funding is more about creating a European transport network than encouraging growth in a single municipality.

It is important to notice that the data used here is quite similar to the data used by Melo et al. (2010) and Holl (2004A), since we analyse the location of new manufacturing establishments in almost 8,000 Spanish municipalities, which have an average size of 4,598 inhabitants.[6] Therefore, the characteristics of our data set mean that endogeneity problems are not likely to occur. Even so we have tried to account for it by using instrumental variables in a strategy that is similar to that of Duranton and Turner (2010). Concretely, if we want to infer the effect of accessibility (i.e., transport infrastructures) over firm location it is important to take into account that investment in transport infrastructures could be decided trying to improve firm attraction by some areas or depending on previous firm entry decisions. In order to overcome this problem, we need an instrument able to affect firm location decisions only through its effect on transport infrastructure conditional to other control variables.

To be more specific, we used the population change between 1970 and 1991 (POP_GROWTH_70_91) because it can be a good predictor of the highway system in the nineties. The correlation between the measure of accessibility in 1991 and population growth between 1970 and 1991 is not too large (-0.224) but it illustrates that trends in population change can be an indicator of the state of the highway system.

[6] Most of these municipalities (around 6,000) have between 100 and 4,999 inhabitants and only two have more than 1 million.

Table 1 shows the results of an OLS regression of accessibility on the instrumental variables and controls.

[INSERT TABLE 1]

The first column includes a simple specification that regresses accessibility against the instrument and the density of value added (DENSITY_GDP), while in second, third and fourth columns we include additional socio-economic characteristics of municipalities (population in 1991 –POP_1991-, diversity index –DIVERSITY- and percentage of jobs in services –JOB_SERVICES-). We should point out that the instrumental variable is significant and has the expected sign and, consequently, it is appropriate for our purposes.

3. Exploratory Spatial Analysis of the location of manufacturing establishments

In this paper we use municipalities[7] as the spatial units. We rejected larger spatial units such as European NUTS 3 and did not consider other smaller units, such as *comarcas* or metropolitan areas, since there is no standard classification of such areas throughout the country.

The Spanish highway network was extended quite considerably during the last two decades of the 20th century,[8] and we assume that these changes improved accessibility to the network and modified the location decisions of manufacturing firms. In this section we carry out an exploratory analysis to test whether the creation of new manufacturing establishments followed a spatial pattern during the period 1991-1995. We have chosen this period because most of the HN building program had been

[7]According to the 1990-91 Census there were 8,090 municipalities in Spain in that period. Of these, only 605 accounted for 76.28% of the Spanish population (total Spanish population was 41 million). Thus the average population of Spanish municipalities was relatively low: 5,192 inhabitants. Both employment and establishments are also concentrated in the larger municipalities.

[8] The main targets of the program were to improve the accessibility of municipalities to high capacity roads (dual carriageways and motorways); to Madrid; to the main economic centres (municipalities larger than 150,000 inhabitants in 1991); and to the European high capacity road network, through Irun and La Jonquera (Pablo-Martí and Myro, 2006). A summary of the effects of the Spanish motorway building programme can also be seen in Holl (2007).

completed by the mid-1990s. Before carrying out the spatial exploratory analysis we summarized the creation of manufacturing establishments in Spanish municipalities (see Table 2).[9] The data on new manufacturing establishments is taken from the Spanish Registry of Manufacturing Establishments (REI).[10]

[INSERT TABLE 2]

As we have explained above, we selected ten specific industries with differences, among other things, in technology, productivity, labour demand and markets (we expect these industries to be influenced by different location determinants): Food, drinks and tobacco; Clothes and leather; Wood and furniture; Printing and paper; Chemistry; Other non metallic minerals; First transformation of metals; Machinery; Computer and office equipment; Electric and electronic equipment and Transport equipment. As can be seen in Table 2, traditional manufacturing activities, such as Food, Clothes, Wood and furniture, Other non metallic minerals and First transformation of metals account for almost 76 % of the total new manufacturing establishments.

3.1 Methodology

The exploratory analysis carried out in this section consists of cartograms and spatial autocorrelation statistics which are applied to the creation of manufacturing establishments and to location quotients for every manufacturing industry considered.[11] A cartogram is a map in which the municipalities are replaced by circles. The area of the circles is proportional to the value of a selected variable. The circles may be highlighted in white (zero values), in green (around the mean value), or in red (high values). These cartograms show where the establishments created between 1991 and

[9] We have used data from almost all Spanish municipalities. Because of their non spatial contiguity we have left out municipalities located on islands, and outside Europe. Municipalities with not enough data or with no reliable data have also been left out.
[10] Before starting their activities, firms must provide some basic data to REI such as expected employment, expected investment or electrical power. See Mompó and Montfort (1989) for a description of the dataset.
[11] The data source for industry specialisation is the Censo de Locales 1990 (Establishments Census 1990). The data source for manufacturing location is the Registro de Establecimientos Industriales, REI (Spanish Registry of Manufacturing Establishments).

1995 are located, and how important the municipalities are as a location for each industry. This importance is also shown in the cartograms for industry specialisation in 1990, which is measured by the location quotient, defined as follows:

$$LQ_{im} = (E_{im} / E_i)/(E_M / E_T) \quad , \tag{1}$$

where E_{im} represents total employment in manufacturing activity *m* in municipality *i*, E_i represents total employment in municipality *i*, E_M represents total national employment in manufacturing activity *m*, and E_T represents total national employment in all manufacturing activities. Therefore, a large red circle means that a given municipality is more specialised in a given industry than the national average. Comparison of location cartograms with location quotient cartograms tell us whether the more specialised municipalities are also the ones in which most new establishments are located.

The spatial autocorrelation statistics calculated in this section are the BB Joint Count test and Moran's I. The BB Joint Count test is applied to the location decision: that is, whether new manufacturing establishments have been created for a given industry or not. Moran's I will be applied to test whether new establishments and municipality industry specialisation is autocorrelated in space, and also to test the geographical scope of the creation of new manufacturing establishments.

The value of the BB Joint Count test shows the number of times that a municipality in which the location decision has been implemented is contiguous to another municipality where new manufacturing establishments have also been created. It is defined as follows (Cliff and Ord, 1980)[12]

[12] As far as we know the BB Joint Count test has not been used to study industrial location before. However, this test is widely used in other disciplines such as Natural Sciences and Geography. See Bell, Schuumarn and Hammeed (2008) or Burt, Barber and Rigby (2009).

$$BB = (1/2)\sum_i \sum_j w_{ij} x_i x_j, \tag{2}$$

where w_{ij} is the i-j_{th} element of a spatial weights matrix (W) and x is a binary variable which is set to 1 if new establishments of a given manufacturing activity have been created over a period of time, and x is set to 0 otherwise; i and j are municipalities, and w_{ij} is the *i-jth* element of a binary spatial weights matrix W, which is set to 1 if municipalities i and j share a common frontier, and w_{ij} is set to 0 otherwise.

Moran's I statistic shows whether there is a spatial autocorrelation in continuous variables. It is defined as follows[13]:

$$I = N/So \sum_i \sum_j w_{ij}(x_i - u)(x_j - u) / \sum (x_i - u)^2, \tag{3}$$

where N is the number of observations, w_{ij} is the element in the spatial weights matrix (W) corresponding to the observation pair i,j (this is set to 1 if municipality i and municipality j share a common border and are therefore neighbours, and to 0 otherwise); x_i and x_j are observations for locations i and j (with mean u), and So is a scaling constant: ($So = \sum_i \sum_j w_{ij}$). However, if both municipality specialization and new manufacturing establishments are spatially autocorrelated, we will use distance-based matrices to test the geographical scope of the creation of manufacturing establishments. For each industry we will start by setting w_{ij} to 1 if the distance between municipality i and j is longer than 5 kilometres and shorter than 10 kilometres, and to 0 otherwise. If the statistic is significant we will consider the following distance band (10 to 15 kilometres)[14] and so on. When the statistic is no longer significant for a given distance band we will assume that the geographical scope of the creation of new manufacturing establishments will end in the lower band of that matrix. Therefore, the elements of the

[13] Moran's I statistic – see Moran (1948) or Anselin (1988) for a detailed analysis – is by far the best known statistic test for spatial autocorrelation.
[14] We do not include previous distance bands in order to avoid spurious spatial autocorrelation.

spatial weight matrices used in the regression analysis will be set to 1 if the distance is less than that lower band and to zero otherwise.

Significant and positive z-values for the spatial autocorrelation statistics – positive spatial autocorrelation – show agglomerative behaviour. That is, for a given industry, similar location decisions, similar creation of establishments, and similar municipality specialization are so spatially clustered that mere chance is not a possible explanation. Therefore, most of the municipalities that are specialised and involved in the creation of establishments should be neighbours. This behaviour may be caused by external economies, such as location or urbanization economies, and, according to the so called New Economic Geography, low transport costs: that is, by better accessibility (Fujita et al, 1999).

3.2 Results

Our exploratory spatial analysis of the creation of new manufacturing establishments and of the manufacturing specialization of Spanish municipalities is shown in tables 3 to 12. Each table deals with one manufacturing industry. They include the following figures and statistics: cartograms for new manufacturing establishments (figures 3a to 12a) and for the location quotient of the municipalities (figures 3b to 12b); the BB joint count test for location decisions (tables 3a to 12a); Moran's I for the location quotient (tables 3b to 12b) and for the geographical scope of the creation of new manufacturing establishments (tables 3c to 12c).

As can be seen in figures 3a to 12a most manufacturing establishments are created in the centre of Spain and in the coastal areas. Madrid (the capital of Spain), Barcelona and

Valencia (the main Mediterranean agglomerations), and the surroundings of these cities are the most dynamic areas. Specialization cartograms (figures 3b to 12b) show that these areas are also the ones where location quotients are higher for most industries. The importance of these areas is overwhelming, although in some industries municipality specialization is more spatially spread, such as Food and drinks, Clothes, Wood and furniture, First transformation of metals or Machinery (figures 3b, 4b, 5b, 9b and 10b).

The cartograms for the creation of manufacturing establishments and location quotients suggest that these variables are spatially autocorrelated. Before estimating Moran's I statistic for these variables we will test whether the decision to create one or more manufacturing establishments in a municipality and a given industry is related to the location decisions taken in neighbouring municipalities. In order to do so, we have estimated the BB joint count test for location decisions taken both in the whole period (1991-1995) and in every single year (tables 3a to 12a). Results show that location decisions in a municipality are related to the location decisions taken in neighbouring municipalities. As expected, the number of contiguities, BB values (tables 3a to 12a), is usually larger in the industries in which most manufacturing establishments were created (Table 2).

Since the BB joint count test is based on binary variables, no matter how many manufacturing establishments were created, we also estimated Moran's I statistic for the number of establishments created throughout period. We also used a first order contiguity spatial weights matrix. Results (tables 3b to 12b) show that the creation of manufacturing establishments is spatially autocorrelated in all industries considered.

In order to test whether this spatial pattern may be due to the economic advantages derived from localization economies we applied Moran's I test to the location quotient, a simple measure of specialization. Location quotients for all the industries, except food under the normal assumption, are also spatially autocorrelated (tables 3b to 12b). Therefore, we cannot reject the hypothesis that the spatial pattern of new manufacturing industries is due to agglomeration economies. The lack of significance of Moran's I for the Food location quotient under the normal assumption may be explained by the fact that this industry is widely spread across Spain.

Spatial autocorrelation statistics on location decision, industry specialization, and establishment creation were estimated using a first order contiguity spatial weights matrix. However, as suggested by the cartograms (figures 3a to 12b), the geographical scope of these phenomena is larger than first order contiguity. Therefore we also estimated Moran's I statistic on the creation of establishments using distance-based matrices. The results (tables 3c to 12c) show that the geographical scope of the creation of establishments differs among industries. It ranges from 35 kilometres for Printing to 145 kilometres for Other non metallic minerals. Some of the high value added industries, such as Machinery or Electric and electronic equipment, show shorter geographical scopes than those of the low value added industries, such as Food or Other non metallic minerals. As can be seen in Table 2, fewer municipalities have entries in high value added industries than in low value added industries. Both the reduced geographical scope and the limited number of locations for high value industries are consistent with location theory which states that "higher value goods tend to be produced or marketed in a smaller range of locations than low-value goods, thereby increasing the market areas and the shipment distances of these goods" (McCann, 2001, p. 17).

Our results show intra-industrial agglomerative spatial patterns for all the industries. For each industry new establishments tend to locate in neighbouring municipalities and highly specialised municipalities are spatially clustered. On the one hand, this spatial behaviour, which is reflected through statistically significant spatial autocorrelation indicators, may be due to the benefits derived from specialization: that is, Marshallian externalities. In fact these spatial patterns resemble the Marshallian industrial districts identified and analysed in Boix and Trullén (2011) and in Molina-Morales and Martínez-Fernández (2006). On the other hand, the existence of spatial autocorrelation suggests that spatial techniques should be used to analyse the location of these industries, to avoid the consequences of ignoring spatial autocorrelation, and to test the geographical scope of agglomeration economies.

4. Data, model and results

4.1 Variables and data[15]

As a dependent variable, we use LOC_{im}, which accounts for the number of manufacturing establishments (i.e., this is a count variable) created in municipality *i* and in manufacturing industry *m* over the period 1991-1995.[16]

According to the neoclassical approach (Hayter, 1997), location determinants are usually grouped into categories such as supply factors, demand factors and external economies and diseconomies. Accessibility may be considered as a supply factor since

[15] See appendix I for descriptive statistics.
[16] Data on the explanatory variables data mostly come from the *Censo de Locales* 1990 (Establishments Census 1990). Spanish censuses are published every 10 years. *Censo de Locales* 2000 (Establishments Census 2000) data are not available for most municipalities.

it means lower transport costs, but it may also enlarge the geographical extent of externalities. Besides accessibility, the location factors we consider are: human capital; internal market; external economies related to urban agglomeration and external economies related to local specialisation as spatial externalities. We consider that the main contributions of this paper are on the variables side: the internal market variable and our approach to the geographical scope of agglomeration economies, namely interurban agglomeration economies.[17] To sum up, the creation of new manufacturing establishments can be expressed as follows:

$$LOC_{im} = f(ACC_i, HC_i, GDP_i, DI_i, LQ_{im}, IAF_i)\,, \qquad (4)$$

where ACC_i is the accessibility indicator for municipality *i*: that is, the number of minutes needed to access the highway network (motorways and dual carriageways) from municipality *i*. It is constructed using Geographical Information Systems[18] and, since better accessibility means less travelling time, it is expected to be negative.

The human capital index, HC_i, is defined as the percentage of the population the percentage of the population who have completed at least their secondary education in municipality *i* in 1991. We assume that locations with skilled workers will be preferred, even if this implies higher wages, so HC_i is expected to be positively related to location decisions. The HC_i data is taken from the 1991 Spanish Population Census (*Censo de Población 1991*).

The internal market is measured by GDP_i (Gross Domestic Product of municipality *i*), which measures the strength of the economy of a municipality, its internal potential

[17] Local tax data are not available for reasons of statistical secrecy. If we used provincial NUTS 3 data to act as a proxy for local data on taxes, labour costs or land prices, we would fall into an ecological fallacy and have Modifiable Areal Unit problems (see Anselin, 1988, Arbia, 1989 or Pablo-Martí and Muñoz-Yebra 2009) for a more detailed discussion of this topic). A detailed analysis of location determinants can be found at Guimarães *et al* (2004), Figueiredo *et al* (2002) and Guimarães *et al* (2000).
[18] See Pablo-Martí and Myro (2006) for a detailed analysis of this indicator.

market, and its purchasing power. This variable is also an indicator of input-output linkages, since municipalities with the largest GDP_i (main cities) are the main industrial suppliers and customers. GDP_i[19] is taken from Alañón (2001, 2002), is measured in euros (millions), and is expected to be positive.

DI_i is a manufacturing diversity index for municipality *i*. Specifically, DI_i tries to proxy spatial externalities related to urban agglomeration such as Jacobs external economies (Glaeser et al., 1992), and the so-called urbanization economies (Richardson, 1978). Bigger cities tend to be more diverse than smaller ones, and firms in diverse cities benefit from a more competitive environment and other advantages such as non-industry-specific and non-traded local inputs. This index is based on the proposal by Duranton and Puga (2000) which corrects the differences in the Hirschman-Herfindahl index regarding employment percentages per sector at national level:

$$DI_i = 1 / \sum_m / s_{im} - s_m / \ , \tag{5}$$

where s_{im} is the share of manufacturing activity *m* in manufacturing employment in municipality *i*, and s_m is the share of manufacturing activity *m* in total national manufacturing employment. The sign is expected to be positive and the statistical source is the 1990 Spanish Establishments Census (*Censo de Locales* 1990).

Local specialisation, measured by (LQ_{im}) generates Marshallian externalities.[20] LQ_{im} measures the relative specialisation of municipality *i* in industry *m* and is the location quotient defined in expression (1). Although it is reasonable to expect a positive sign

[19] Since there are no official statistics on GDP at municipal level we used the ones estimated in Alañón (2001). Municipal figures were estimated indirectly using Spatial Econometrics to deal with spatial autocorrelation problems. More information can be found in Alañón (2002).

[20] These can be economic advantages derived from a local skilled-labour pool, local information spillovers and non-trade local inputs, and related concepts such as localization economies (Richardson, 1978) or, following Glaeser *et al* (1992), MAR external economies (named after Marshall, Arrow and Romer), such as industry specific externalities in non-competitive environments.

(i.e., extant specialisation in the same manufacturing activity can positively affect entries of these types of establishments), it is also possible that the effect on entries is negative. Since higher LQ_{im} may be caused by a large number of small firms or by a small number of large firms, it may be an indicator both of concentration or internal returns of scale. Our employment data is taken from the last Spanish Establishments Census (*Censo de Locales* 1990).

Finally, we considered the geographical scope of agglomeration economies (interurban agglomeration forces: IAF_i), which was discussed in sections 1 and 2. Broadly speaking, in this paper we consider that these externalities are the interurban effects of the location determinants described above. It is therefore reasonable that decision makers take into consideration not only the internal characteristics of a given location but also the characteristics of its neighbouring area. *Ceteris paribus,* decision makers prefer locations that have the following characteristics: good accessibility, nearby municipalities that provide a qualified labour force and public goods and services, good markets for their products and spatial externalities (rather than more isolated locations or locations without such good neighbours). In line with other location analyses such as Autant-Bernard (2006) or Alañón et al. (2007), and other non location studies on the spatial and sectoral impacts of agglomeration economies such us Van Soest (2006), Van Oort (2007) and Bishop and Gripaos (2010), we apply spatial econometrics techniques to measure the effects of the IAF_i and to deal with spatial autocorrelation properly.

As will be shown in the next section, the IAF_i indicator is proxied by the spatially lagged independent variables WHC_i, WLQ_i, WDI_i and $WGDP_i$[21], where W is a binary

[21] Autant-Bernard (2006), who analyses the location of R&D establishments in French NUTS 2 using a conditional logit model, also includes the spatially lagged explanatory variables to deal with spatial dependence.

matrix based on the results in section 3.2 on the geographical scope of agglomeration economies (tables 3 to 12). That is, each element of the spatial weight matrix, w_{ij} is set to 0 if municipalities i and j are far from a threshold kilometric distance and to 1 otherwise. These kilometric distances are: 95 for Food and tobacco; 105 for Clothes and leather; 70 for Wood and furniture; 35 for Printing and paper; 105 for Chemistry; 145 for Other non metallic minerals; 90 for First transformation of metals; 55 for Machinery; 50 for Electric and electronic equipment and 135 for Transport equipment.

4.2 Econometric specification

Most recent contributions to location analysis use count data models to model the location decisions of new firms.[22] These models have some advantages when using typical location data at the spatial level in which the analysis is conducted (usually local). That is, they can deal with the "zero problem",[23] the situation in which a large number of territorial units receive no new establishments (which is typical when the territorial units are small, as municipalities are). The dependent variable in count data models is the number of firms located in each municipality, so it is useful to know not only how many times a municipality has been chosen by new firms, but also which municipalities have not been chosen by any firm.

Specifically, the number of firms located in each municipality is modelled as a Poisson-distributed random variable in which the parameter λ_i is related to the vector x_i which measures local characteristics. Following Cieślik (2005), we assume that the probability of attracting y_i firms to a municipality depends on the specific attributes of the municipality:

[22] See Arauzo-Carod (2008) for a review of the methodological issues regarding industrial location literature.
[23] See Cameron and Trivedi (1998) for a detailed analysis of the "zero problem".

$$\Pr(y_i|x_i) = \frac{e^{-\lambda_i}\lambda^{y_i}}{y_i!}, \quad y_i = 0,1,2,..., n, \tag{6}$$

where λ_i is dependent on the vector of site characteristics. Concretely, the local characteristics of municipalities (x_i) and neighbouring municipalities (wx_i) are proxied by the vector of explanatory variables:

$$\ln \lambda_i = \beta' x_i + \rho' wx_i, \tag{7}$$

and where the vectors of coefficients of explanatory variables to be estimated are β (municipalities) and ρ (neighbouring municipalities). Therefore, we assume that the location decisions of firms will depend not only on the characteristics of the municipalities in which a firm locates but also on the characteristics of neighbouring municipalities: that is, we consider the neighbouring municipalities as the geographic scope of agglomeration economies.

Additionally, the Poisson model (PM) assumes that conditional mean and variance functions equal λ_i:

$$E[y_i|x_i] = \mathrm{var}[y_i|x_i] = \lambda_i \tag{8}$$

There is a generalized version of the PM (the Negative Binomial model: NBM) that introduces an individual unobserved effect into the conditional mean:

$$\ln \lambda_i = \beta' x_i + \rho' wx_i + \varepsilon_i, \tag{9}$$

where ε_i shows either a specification error or some cross-sectional heterogeneity. Exp (ε_i) follows a gamma distribution with mean 1 and variance α.

In location analysis conditional variance is usually greater than the conditional mean ("overdispersion"), because firm entries are usually clustered in bigger areas. A solution for “overdispersion” is to use an NBM, which allows the variance to exceed the mean. In the NBM[24] the variance equals:

$$\operatorname{var}[y_i|x_i] = E[y_i|x_i]\{1+\alpha E[y_i|x_i]\} \qquad (10)$$

If α equals zero, the conditional variance is equal to the conditional mean and the PM and the NBM are the same. If there is spatial autocorrelation, ε does not follow a normal distribution in limited dependent models. Therefore, the resulting multivariate specification is intractactable in standard PM.[25] Spatial autocorrelation not only impacts the precision of the estimates but also the point estimates (Fischer and Griffith, 2008). These are the reasons why we estimate NBM with spatially lagged explanatory variables. On the one hand, they account for spatial dependence and, on the other, they may help to explain the economic causes or the economic meaning of spatial autocorrelation.

4.3 Results

The results of our estimations are summarized in Table 13. First of all, we should stress that the accessibility (ACC) coefficient is significant and shows the expected sign in almost all of the econometric specifications. This means that the higher accessibility is, the higher the location of new manufacturing plants will be, as has been previously demonstrated for Portugal (Holl, 2004b), Spain (Holl, 2004a) and Catalonia (Arauzo-Carod, 2005).

[INSERT TABLE 13]

[24] Concretely, this is the type II parameterization of the Negative Binomial model. See Cameron and Trivedi (1998) for further details.
[25] However, Kaiser and Cressie (1997) developed a Poisson auto-model which allows positive spatial dependencies in multivariate count data by specifying conditional distributions as truncated or Winsorized Poisson probability mass functions. Poisson spatial interaction models are estimated in Lesage et al (2007) and in Fischer and Griffith (2008) to analyse origin-destination patent citation data.

The results on the accessibility variable clearly show that a road connection between cities plays a key role in location decisions in all industries. Consequently, public policies about where and how to build new routes (and, particularly, new highways) undoubtedly have an influence on these decisions. That is, when the time taken to access the HN from a municipality increases, the attractiveness of this municipality in terms of the location of new manufacturing establishments decreases. This negative effect of accessibility on location is common in location analyses (see, for example, Holl, 2004a, 2004b; List, 2001; and Coughlin and Segev, 2000).

The coefficients related to the internal characteristics of the municipality (human capital, internal market and the spatial economies derived from diversity and industry specialisation) are highly significant and show the expected sign for most specifications. Concretely, new establishments are positively attracted by skilled labour (HC), industrial diversity (DI) and local specialisation (LQ).[26] Surprisingly, the weight of the local economy (measured according to local GDP) does not play a significant role in new plant decisions, except for Wood and furniture (increases entries) and First transformation of metals (reduces entries).

Despite previous results, empirical evidence on the internal characteristics of municipalities is not as clear as it is for accessibility. Human capital (HC), for instance, is one of the most controversial location determinants since scholars have found that it has both a positive and a negative effect on location decisions. Empirical industrial location literature has found that although firms prefer to be located in areas with good accessibility to educated workers (Coughlin and Segev, 2000; Woodward, 1992), higher

[26] A municipality may be both specialized in a given industry and industrially diversified. See Duranton and Puga (2000) for further details.

wage areas (i.e. areas with a high rate of skilled labour) also have a negative effect on new firm entries (List, 2001; Friedman et al., 1992; Papke, 1991). Diversity (DI) is another local characteristic whose effect as a locational determinant is not clear. Although it has been said that a specialised environment is preferred in order to benefit scale economies (Henderson et al., 1995), some authors argue that the greater the diversity of activities at a site, the greater its potential growth (Glaeser et al., 1992; Jacobs, 1969).

We assume that some of the heterogeneity of empirical results can be explained by the geographical areas considered when discussing the effects of local characteristics on entries.[27] Unfortunately, this issue has not been addressed by most empirical contributions on industrial location. In an attempt to deal with these shortcomings, we consider that both local characteristics and the situation and events in neighbouring municipalities need to be taken into account. Therefore, the geographic scope of agglomeration economies also seems to play a role in the location of new plants. Accordingly, we have also estimated the spatial lagged variables for skilled labour (WHC), industrial diversity (WDI), local specialisation (WLQ) and weight of local economy (WGDP).

The results for these spatially lagged variables show some spatial-specific effects. Concretely, the spatial range of explanatory variables is clearly not the same, since their effects at the strictly local level and the extended geographical level are different. Human capital (HC), for instance, shows a positive and significant effect for all industries (except for First transformation of metals) at a local level, while its effect is negative (except again for First transformation of metals) for areas larger than a

[27] See Pablo-Martí and Muñoz-Yebra (2009) for a discussion on this topic.

municipality, which means that if a municipality is surrounded by other municipalities with highly skilled individuals, there is a negative influence on firm entries. An alternative explanation, however, could be that spatially lagged human capital indicators do not measure local labour markets properly.

The opposite results obtainedfor local (LQ) and spatially lagged specialisation (WLQ) variables are more striking. While the variable is positive at a local level, the spatially lagged location quotients for Food, Printing, Other non metallic minerals and First transformation of metals have a negative effect, suggesting that establishments from these industries prefer non competitive environments.

However, diversity (DI) always shows a positive and statistically significant sign in most industries, which suggests that mixing different activities helps to attract new firms. Finally, while the weight of the local economy (GDP) seems not to matter at a local level (firms do not care about local GDP levels), it is a significant characteristic that reduces entries when wider spatial areas are considered (WGDP). This shows that manufacturing plants tend to avoid areas with stronger GDP levels.

To sum up, it seems clear that accessibility has a positive effect on firm location decisions: that is, the greater the municipality's access to the HN, the more firms will be located there. The policy implications of these results are clear, since municipalities are interested in diminishing travel time to such infrastructures. Most of the other local characteristics that have been taken into account (human capital, local value added, industrial diversity and specialisation) also show a largely positive effect on location decisions when measured at a local level, whatever the specific industry the entering establishments belong to. Nevertheless for larger areas, human capital and local specialisation show a negative effect when spatial lags are introduced and weight of local economy only matters (in a negative way) when using the spatially lagged variable. Therefore, it seems that some firms may tend to avoid richer, specialised, or well educated areas (in an attempt to cut down operating costs).

Internal explanatory variables and spatially lagged variables may be contradictory because there are some differences between the real geographical scope of each explanatory variable and the scope estimated for the creation of establishments in section 3.2, but we have left the analysis of this issue for future research.

5. Conclusions

The aim of this article was to analyse how agglomeration economies and accessibility shape the location determinants of new manufacturing establishments in ten different industries. Exploratory spatial analysis shows that most new manufacturing establishments have chosen specialised municipalities, located mostly in the centre and the coastal areas of Spain. Location decisions, municipality specialization and the creation of manufacturing establishments are positively spatially autocorrelated, which corroborates the supportive environment thesis. The geographical scope of the creation of manufacturing establishments ranges from 35 to 145 kilometres (depending on the industry), and high value added industries usually have shorter scopes than low value added industries. These results are of interest for policy makers, since the process of agglomeration formation is dependent on local resources and processes, and policy interventions may play an important role in stimulating the development of new agglomerations (O'gorman and Kautonen, 2004).

Endogeneity issues were discussed before the role of accessibility was tested using Negative Binomial estimations with local and spatially lagged explanatory variables. Results are consistent with the predictions of New Economic Geography because greater accessibility means lower travel costs and makes external scale economies more feasible, thus favouring agglomeration. Despite the positive effects of accessibility, it should be borne in mind that investment in infrastructure could have conflicting territorial effects. On the one hand, extending the HN may increase the accessibility of nearby municipalities, thus making them more attractive potential locations. But on the other, firms may leave their former locations and move to municipalities whose accessibility has significantly increased. However, the direction of these migrations is not obvious. Some firms may leave rural locations that are far from the HN. Others may leave well-located large agglomerations in order to avoid negative externalities, such us congestion or higher land prices. Any empirical approach to the causal relationship between accessibility and firm location should therefore also consider these negative effects.

The agglomerative behaviour revealed by the exploratory analysis may be due to interurban agglomeration forces, improved accessibility, natural advantages or other causes. Estimation results suggest that the geographical scope of agglomeration economies is larger than suggested in previous studies by Rosenthal and Stange (2003), Viladecans (2004), Jofre-Montseny (2009), Duranton and Overman (2002) or Van Soest et al (2006). These results also show that the source of these interurban externalities may be manufacturing specialisation (which may have positive or negative effects, depending on the industry), and manufacturing diversity.

Finally, this paper contributes to the empirical literature on industrial location by highlighting the joint role played by agglomeration economies and accessibility and, above all, by introducing spatial econometric techniques into location analysis. Since there are plenty of spatial phenomena that usual econometric methodologies are not able to deal with, such methodologies help provide unbiased results and better portray (in this case) determinants of location decisions.

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Table 1 Results of accessibility OLS estimation on instrumental and control variables				
	1	2	3	4
POP_GROWTH_70_91	-0.1097*** (0.0204)	-0.1097*** (0.0199)	-0.1111*** (0.0199)	-0.1141*** (0.0199)
DENSITY_GDP	-0.3139*** (0.0164)	-0.4240*** (0.0213)	-0.4180*** (0.0215)	-0.4046*** (0.0217)
POP_1991		0.1815*** (0.0230)	0.2036*** (0.0252)	0.1879*** (0.0255)
DIVERSITY			-0.1646** (0.0767)	-0.1477* (0.0766)
JOB_SERVICES				0.2102*** (0.0580)
Constant	1.9953*** (0.0418)	0.4421** (0.2011)	0.4171** (0.2012)	0.6476*** (0.2103)
R-squared	0.2368	0.2660	0.2682	0.2742
Adj. R-squared	0.2358	0.2646	0.2663	0.2719
F	242.58	188.80	143.08	117.98
Obs.	1567	1567	1567	1567
Source: own calculations. Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1				

Table 2 Manufacturing establishments creation from 1991 to 1995				
Industry	Establishments		Municipalities	
	Number	%*	Number	%**
Food and tobacco	6288	17.43	1749	22.12
Clothes and leather	4557	12.63	1089	13.77
Wood and furniture	6745	18.69	1788	22.62
Printing and Paper	2493	6.91	682	8.63
Chemistry	2276	6.31	795	10.06
Other non metallic minerals	2246	6.22	1064	13.46
First transformation of metals	7557	20.94	1875	23.72
Machinery	2287	6.34	733	9.27
Electric and electronic equipment	817	2.26	351	4.44
Transport equipment	817	2.26	433	5.48
*Establishments created / Establishments created in the ten industries **Number of municipalities where new establishments have been set up / Spanish municipalities considered. Source: REI				

Table 3 Spatial exploratory analysis: Food, drinks and tobacco

Figure 3a New manufacturing establishments cartogram

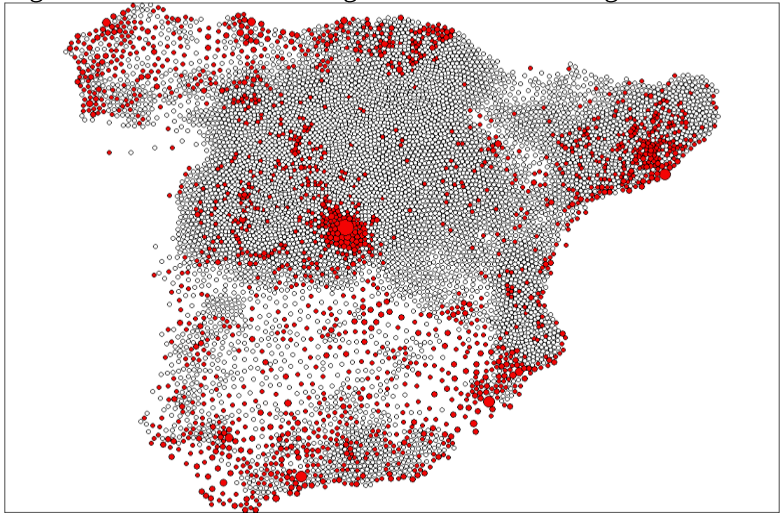

Figure 3b Location quotient cartogram

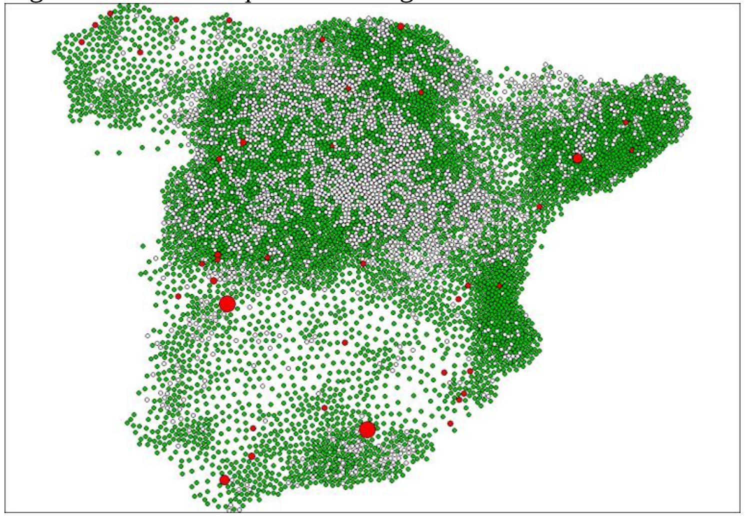

Table 3a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95	2469	39.6	0.000000
1991	555	29.,7	0.000000
1992	492	32.8	0.000000
1993	477	29.4	0.000000
1994	570	32.7	0.000000
1995	622	35.4	0.000000

Table 3b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0,009	1.4	0.166	1.7	0.080	0.03
Establis[5]	0.192	28.5	0.000	33.6	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 3c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.076	9.4	0.000	10-15	0.103	15.9	0.000
15-20	0.105	18.6	0.000	20-25	0.067	13.4	0.000
25-30	0.055	11.9	0.000	30-35	0.032	7.5	0.000
35-40	0.022	5.6	0.000	40-45	0.038	10.0	0.000
45-50	0.032	8.8	0.000	50-55	0.017	5.2	0.000
55-60	0.013	4.1	0.000	60-65	0.013	4.0	0.000
65-70	0.013	4.22	0.000	70-75	0.010	3.3	0.001
75-80	0.012	4.3	0.000	80-85	0.008	2.8	0.005
85-90	0.009	3.1	0.002	90-95	0.007	2.5	0.013
95-100	0.006	2.1	0.033	100-105	0.002	1.0	0.333

Table 4 Spatial exploratory analysis: Clothes and leather

Figure 4a New manufacturing establishments cartogram

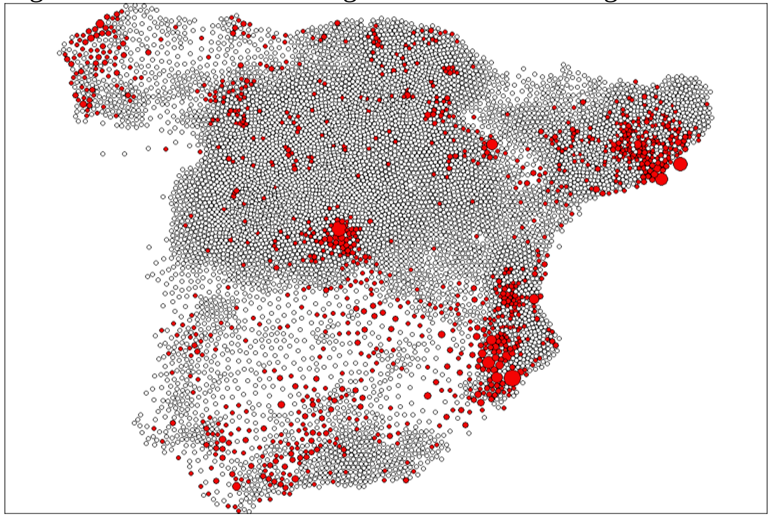

Figure 4b Location quotient cartogram

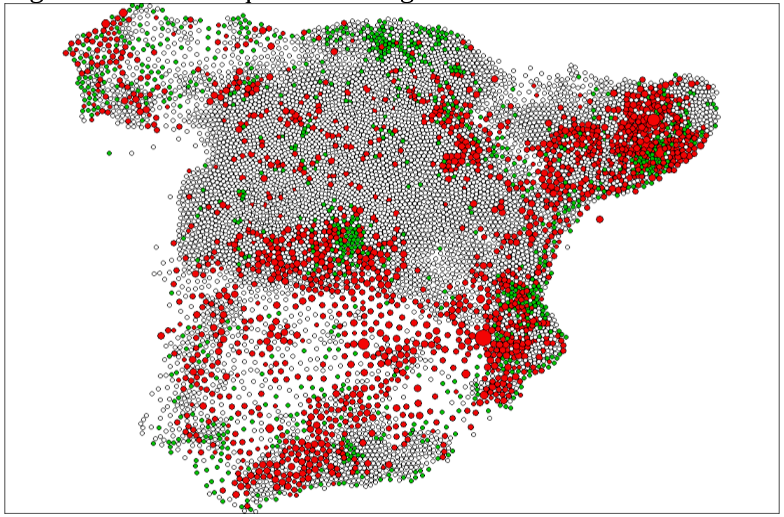

Table 4a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95	1318	41.5	0.000000
1991	415	32.4	0.000000
1992	347	33.1	0.000000
1993	215	26.8	0.000000
1994	232	32.9	0.000000
1995	266	32.3	0.000000

Table 4b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[5]	0.227	33.6	0.000	33.9	0.000	0.01
Establis[5]	0.146	21.8	0.000	23.2	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 4c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0,208	25,6	0,000	10-15	0,058	8,9	0,000
15-20	0,060	10,7	0,000	20-25	0,095	19,0	0,000
25-30	0,058	12,6	0,000	30-35	0,044	10,4	0,000
35-40	0,027	6,8	0,000	40-45	0,041	10,8	0,000
45-50	0,031	8,7	0,000	50-55	0,030	8,8	0,000
55-60	0,024	7,3	0,000	60-65	0,026	8,2	0,000
65-70	0,017	5,5	0,000	70-75	0,009	3,2	0,001
75-80	0,010	3,6	0,000	80-85	0,004	1,5	0,122
85-90	0,005	1,9	0,054	90-95	0,006	2,5	0,009
95-100	0,004	1,8	0,007	100-105	0,012	4,7	0,000
105-110	0,002	1,0	0,287				

Table 5 Spatial exploratory analysis: Wood and furniture

Figure 5a New manufacturing establishments cartogram

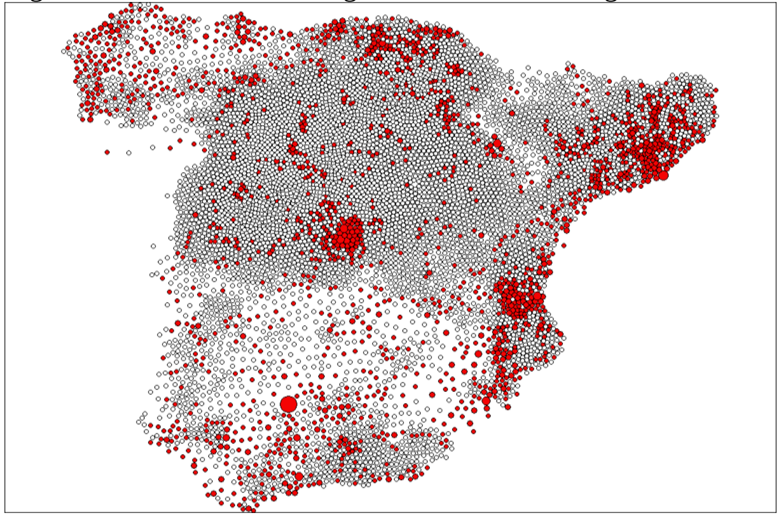

Figure 5b Location quotient cartogram

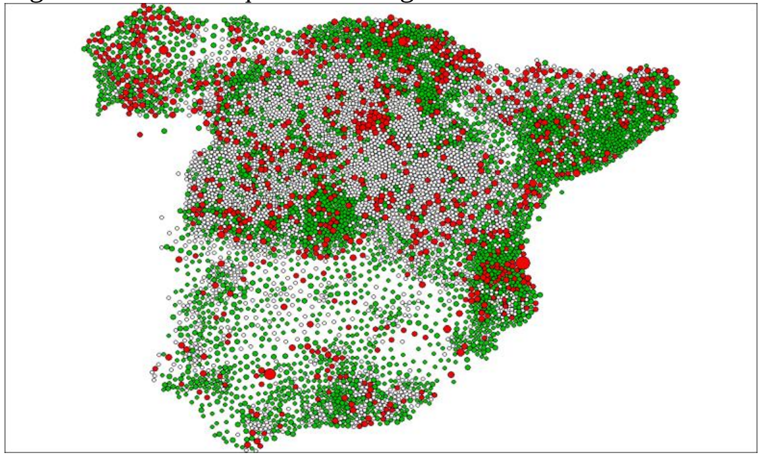

Table 5a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95	2506	38.4	0.000000
1991	694	30.1	0.000000
1992	687	36.0	0.000000
1993	527	31.6	0.000000
1994	373	26.0	0.000000
1995	547	30.4	0.000000

Table 5b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0,114	17,0	0,000	17,1	0,000	0,01
Establis[5]	0,083	12,3	0,000	16,6	0,000	0,01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 5c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.061	7.6	0.000	10-15	0.041	6.4	0.000
15-20	0.026	4.8	0.000	20-25	0.027	5.9	0.000
25-30	0.018	3.9	0.000	30-35	0.013	3.13	0.000
35-40	0.008	2.0	0.040	40-45	0.010	2.7	0.006
45-50	0.012	3.4	0.000	50-55	0.005	1.4	0.158
55-60	0.011	3.2	0.000	60-65	0.08	2.7	0.000
65-70	0.007	2.5	0.000	70-75	0.004	1.6	0.113

Table 6 Spatial exploratory analysis: Printing and paper

Figure 6a New manufacturing establishments cartogram

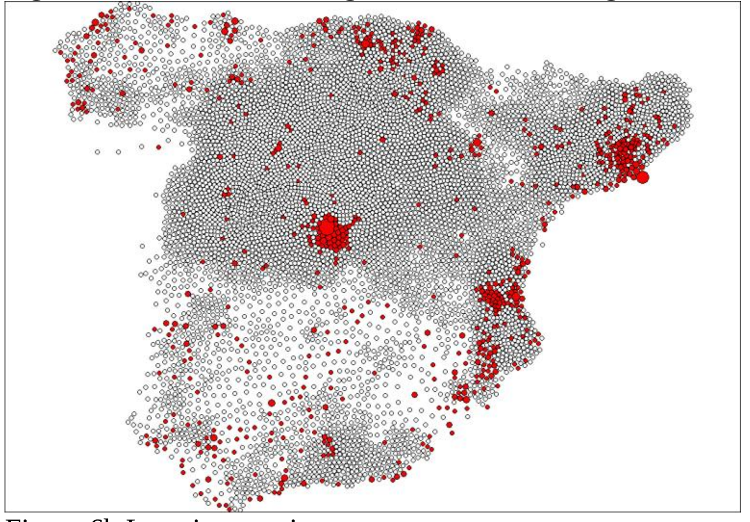

Figure 6b Location quotient cartogram

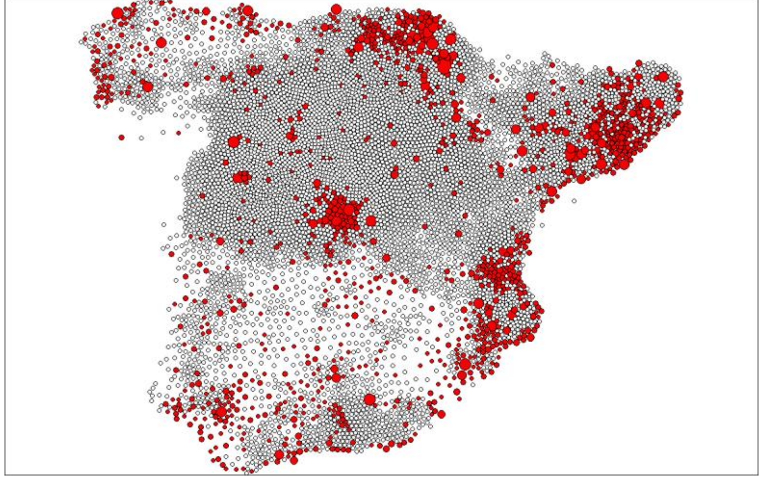

Table 6a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95	41	42.7	0.000000
1991	214	34.9	0.000000
1992	207	36.6	0.000000
1993	161	29.4	0.000000
1994	119	28.9	0.000000
1995	180	32.2	0.000000

Table 6b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0.109	16.2	0.000	16.3	0.000	0.01
Establis[5]	0.192	28.6	0.000	37.6	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 6c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.073	8.9	0.000	10-15	0.102	15.8	0.000
15-20	0.085	15.2	0.000	20-25	0.052	10.5	0.000
25-30	0.23	5.1	0.000	30-35	0.12	2.9	0.003
35-40	0.003	1.0	0.306				

Table 7 Spatial exploratory analysis: Chemistry

Figure 7a New manufacturing establishments cartogram

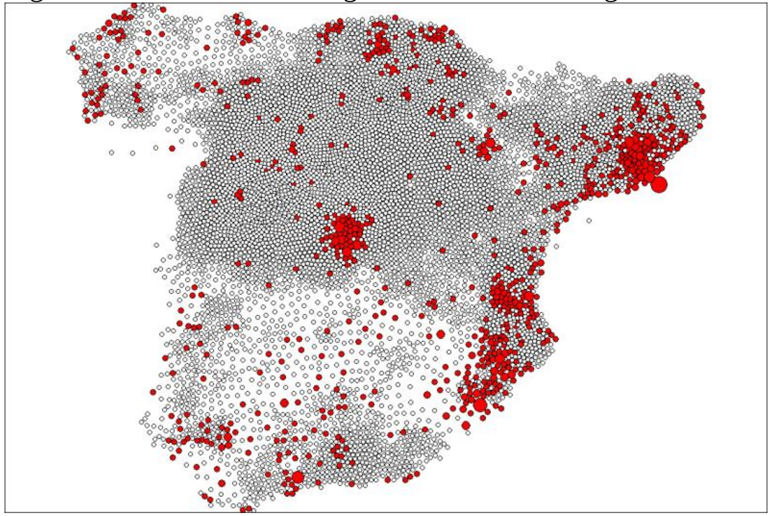

Figure 7b Location quotient cartogram

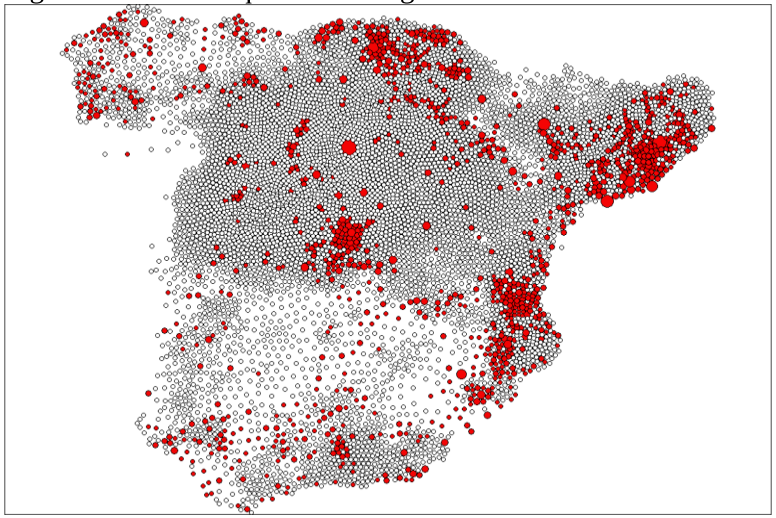

Table 7a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95	925	44.7	0.000000
1991	239	32.0	0.000000
1992	243	35.9	0.000000
1993	187	31.0	0.000000
1994	165	34.1	0.000000
1995	211	33.0	0.000000

Table 7b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0.074	11.1	0.000	11.5	0.000	0.01
Establis[5]	0.031	47.3	0.000	49.1	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 7c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.251	30.8	0.000	10-15	0.188	29.0	0.000
15-20	0.152	27.1	0.000	20-25	0.131	26.2	0.000
25-30	0.092	20.0	0.000	30-35	0.064	15.1	0.000
35-40	0.036	9.1	0.000	40-45	0.065	17.4	0.000
45-50	0.039	10.3	0.000	50-55	0.038	11.1	0.000
55-60	0.023	7.0	0.000	60-65	0.024	7.8	0.000
65-70	0.026	8.4	0.000	70-75	0.014	4.8	0.000
75-80	0.019	6.8	0.000	80-85	0.017	6.0	0.000
85-90	0.025	9.0	0.000	90-95	0.011	4.3	0.000
95-100	0.010	3.9	0.000	100-105	0.005	2.1	0.029
105-110	0.001	0.5	0.550				

Table 8 Spatial exploratory analysis: Other non metallic minerals

Figure 8a New manufacturing establishments cartogram

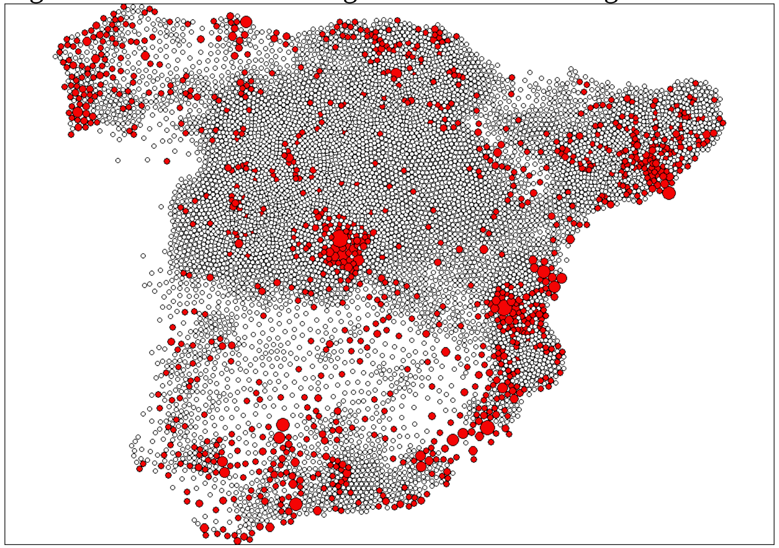

Figure 8b Location quotient cartogram

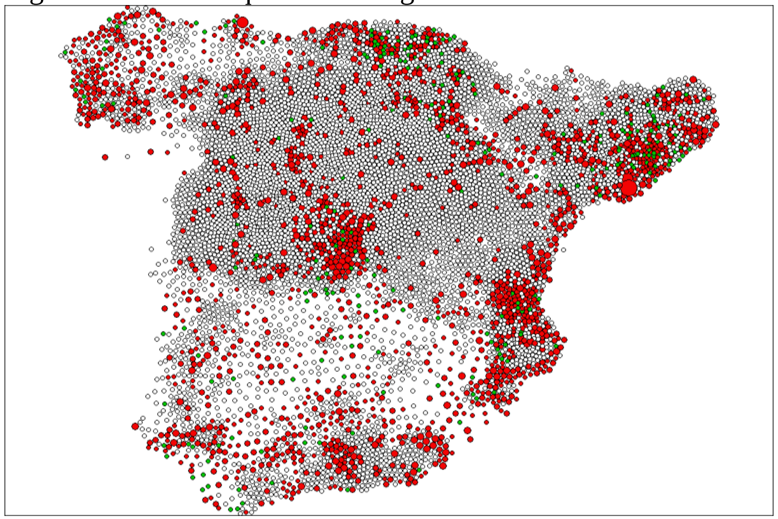

Table 8a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95	1181	36.7	0.000000
1991	265	24.1	0.000000
1992	184	22.2	0.000000
1993	178	23.3	0.000000
1994	117	18.5	0.000000
1995	186	25.5	0.000000

Table 8b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0.110	16.4	0.000	16.9	0.000	0.01
Establis[5]	0.254	37.7	0.000	38.3	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 8c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.148	18.1	0.000	10-15	0.133	20.6	0.000
15-20	0.110	19.6	0.000	20-25	0.110	22.0	0.000
25-30	0.073	15.7	0.000	30-35	0.062	14.7	0.000
35-40	0.037	9.4	0.000	40-45	0.050	13.2	0.000
45-50	0.045	12.4	0.000	50-55	0.047	13.6	0.000
55-60	0.035	10.8	0.000	60-65	0.043	13.3	0.000
65-70	0.035	11.2	0.000	70-75	0.024	8.1	0.000
75-80	0.017	6.0	0.000	80-85	0.022	7.8	0.000
85-90	0.022	8.0	0.000	90-95	0.018	6.7	0.000
95-100	0.017	6.4	0.000	100-105	0.015	5.9	0.000
105-110	0.015	5.8	0.000	110-115	0.015	5.8	0.000
115-120	0.014	5.6	0.000	120-125	0.028	46.3	0.000
125-130	0.017	6.9	0.000	130-135	0.017	7.1	0.000
135-140	0.012	5.0	0.000	140-145	0.010	4.2	0.000
145-150	0.003	1.4	0.137				

Table 9 Spatial exploratory analysis: First transformation of metals

Figure 9a New manufacturing establishments cartogram

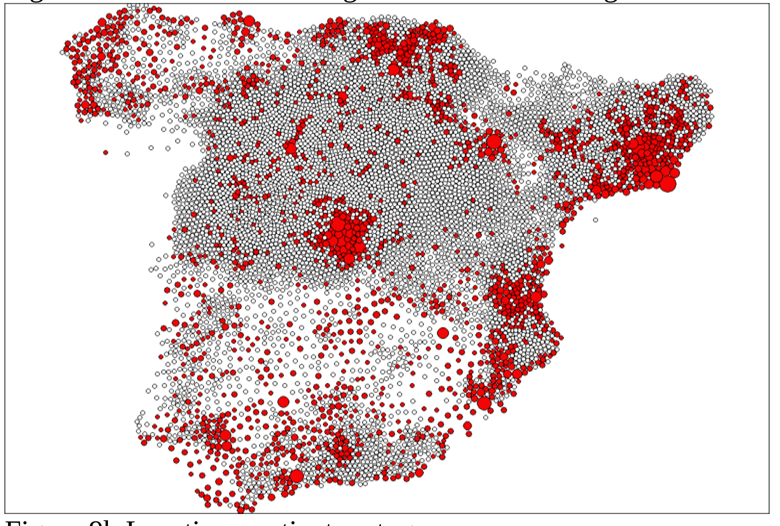

Figure 9b Location quotient cartogram

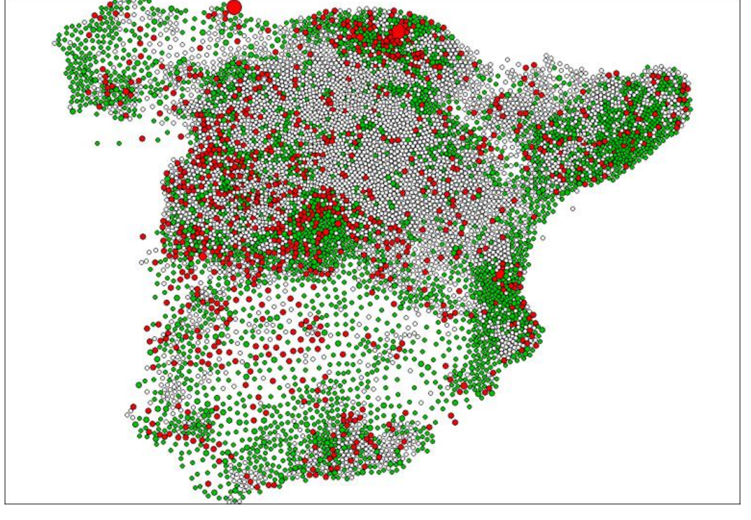

Table 9a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95	2782	41.1	0.000000
1991	888	37.0	0.000000
1992	721	33.0	0.000000
1993	645	36.5	0.000000
1994	519	33.5	0.000000
1995	692	37.6	0.000000

Table 9b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0.049	7.4	0.000	8.0	0.000	0.01
Establis[5]	0.329	48.8	0.000	49.6	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 9c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.271	33.3	0.000	10-15	0.191	29.5	0.000
15-20	0.160	28.5	0.000	20-25	0.120	23.9	0.000
25-30	0.075	16.2	0.000	30-35	0.058	13.7	0.000
35-40	0.035	8.8	0.000	40-45	0.043	11.5	0.000
45-50	0.032	8.9	0.000	50-55	0.016	4.8	0.000
55-60	0.097	2.4	0.000	60-65	0.007	2.3	0.000
65-70	0.008	2.8	0.004	70-75	0.008	2.7	0.005
75-80	0.007	2.6	0.008	80-85	0.005	1.8	0.062
85-90	0.009	3.4	0.000	90-95	0.004	1.6	0.103

Table 10 Spatial exploratory analysis: Machinery

Figure 10a New manufacturing establishments cartogram

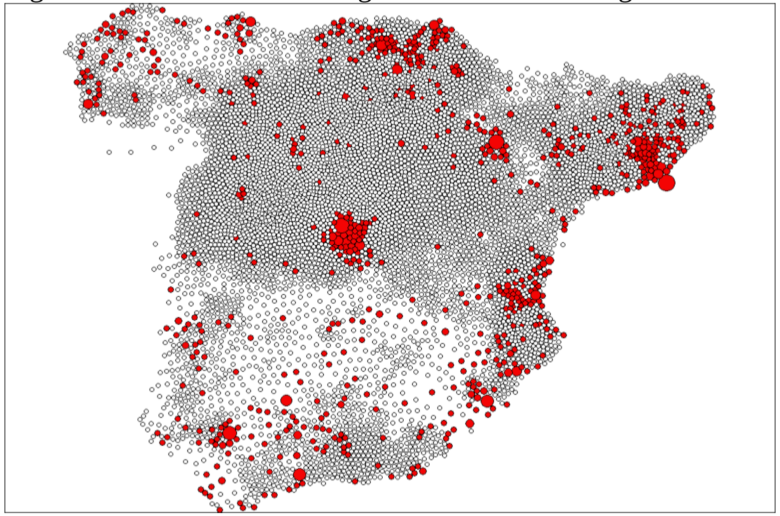

Figure 10b Location quotient cartogram

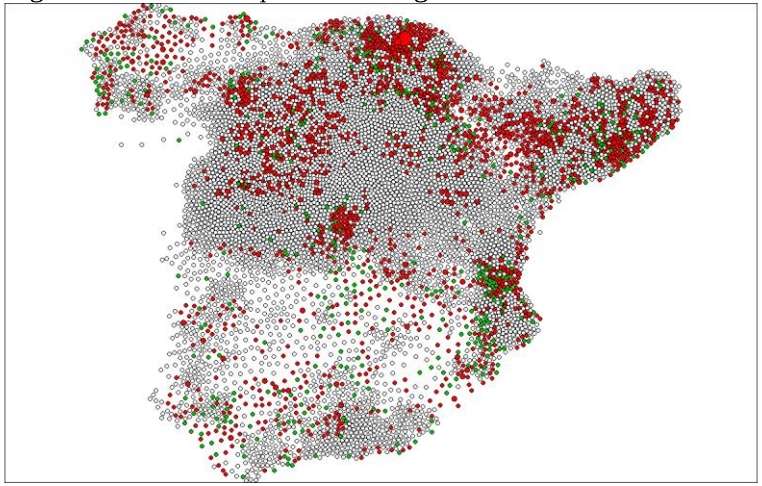

Table 10a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95 810	42,6		0,000000
1991	246	35.9	0.000000
1992	171	28.6	0.000000
1993	151	28.5	0.000000
1994	171	31.5	0.000000
1995	209	33.1	0.000000

Table 10b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0.063	9.4	0.000	18.0	0.000	0.01
Establis[5]	0.228	33.9	0.000	35.0	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 10c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.166	20.3	0.000	10-15	0.127	19.6	0.000
15-20	0.103	18.3	0.000	20-25	0.068	13.0	0.000
25-30	0.037	8.1	0.000	30-35	0.025	6.1	0.000
35-40	0.031	8.0	0.000	40-45	0.011	2.8	0.004
45-50	0.030	8.1	0.000	50-55	0.011	3.3	0.000
55-60	0.004	1.3	0.201				

Table 11 Spatial exploratory analysis: Electric and electronic equipment

Figure 11a New manufacturing establishments cartogram

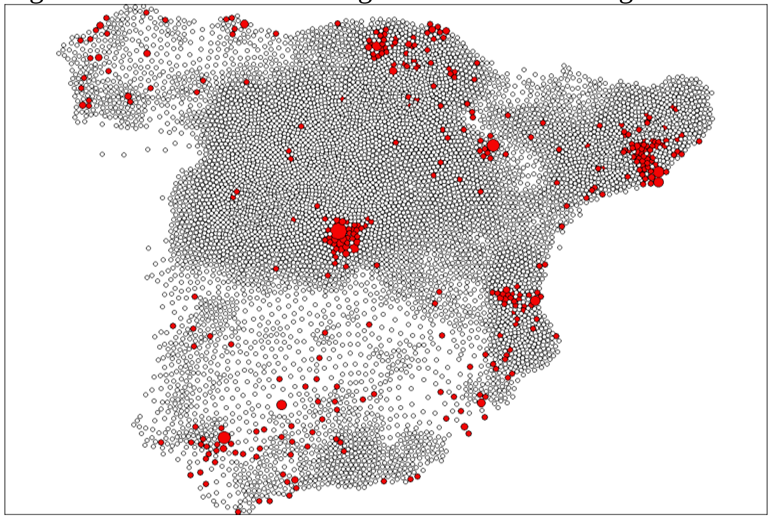

Figure 11b Location quotient cartogram

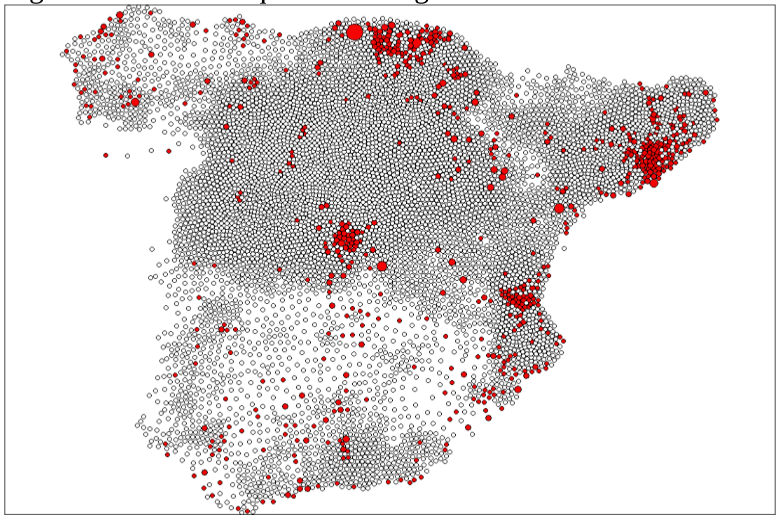

Table 11a BB Joint count test for location decision (neighbouring municipalities)

Year	BB	Z-Value	Prob
1991-95	327	41.2	0.000000
1991	71	25.5	0.000000
1992	51	21.4	0.000000
1993	65	25.7	0.000000
1994	57	31.1	0.000000
1995	56	25.9	0.000000

Table 11b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0.009	1.4	0.149	1.8	0.070	0.01
Establis[5]	0.170	25.3	0.000	27.8	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 11c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.092	11.3	0.000	10-15	0.093	14.4	0.000
15-20	0.071	12.8	0.000	20-25	0.055	11.0	0.000
25-30	0.027	5.9	0.000	30-35	0.010	2.4	0.016
35-40	0.007	1.7	0.008	40-45	0.014	3.8	0.000
45-50	0.009	2.6	0.008	50-55	0.001	0.4	0.656

Table 12 Spatial exploratory analysis: Transport equipment

Figure 12a New manufacturing establishments cartogram

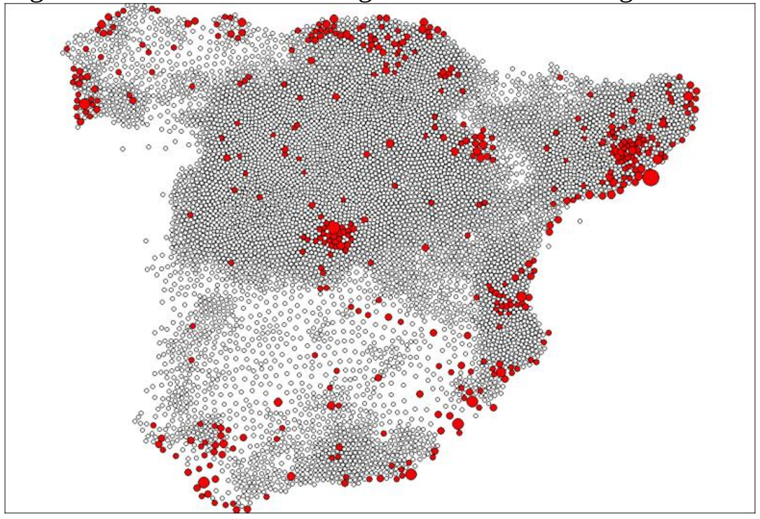

Figure 12b Location quotient cartogram

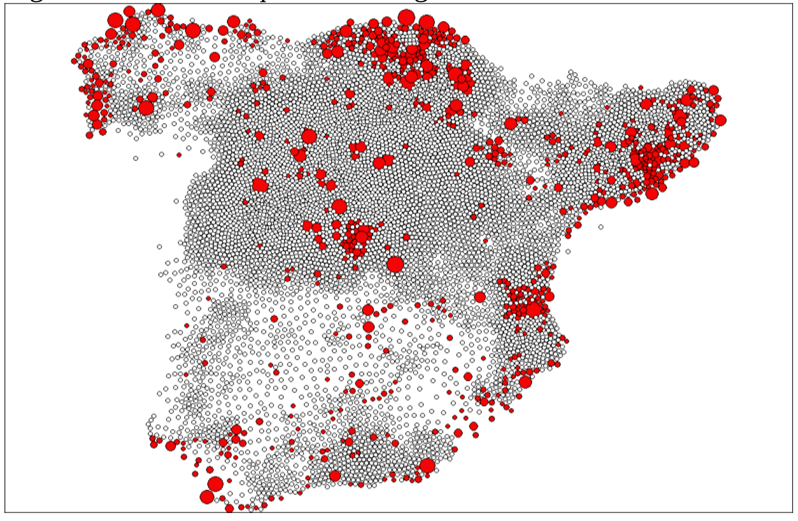

Table 12a BB Joint count test for location decision (neighbouring municipalities)

Year		BB	Z-Value	Prob
1991-95	360	34.3	0.000000	
1991		62	17.2	0.000000
1992		70	18.7	0.000000
1993		42	17.6	0.000000
1994		21	8.9	0.000000
1995		51	20.5	0.000000

Table 12b Moran' I statistic test (neighbouring municipalities)

		Normal[1]		Random[2]		Permut[3]
Variable	I	Z-Val	Prob	Z-Val	Prob	Prob
LQ[4]	0.105	15.7	0.000	15.8	0.000	0.01
Establis[5]	0.206	30.6	0.000	31.4	0.000	0.01

[1]Normal assumption [2]Randomization Assumption [3]Empirical Pseudo-significance based on 99 random permutations [4]Location quotient [5]Establishments created from 1991 to 1995

Table 12c The geographical scope of new manufacturing establishments

Distance band	I	Z Val	Prob.	Distance band	I	Z Val	Prob.
5-10	0.155	19.1	0.000	10-15	0.115	17.8	0.000
15-20	0.092	16.5	0.000	20-25	0.078	15.6	0.000
25-30	0.074	15.9	0.000	30-35	0.036	8.8	0.000
35-40	0.031	8.0	0.000	40-45	0.057	15.1	0.000
45-50	0.021	5.8	0.000	50-55	0.012	3.5	0.000
55-60	0.013	3.9	0.000	60-65	0.007	2.3	0.017
65-70	0.009	3.0	0.002	70-75	0.003	1.1	0.252
75-80	0.006	2.3	0.019	80-85	0.004	1.6	0.098
85-90	0.008	3.1	0.001	90-95	0.011	4.3	0.000
95-100	0.004	1.8	0.067	100-105	-0.001	-0.3	0.702
105-110	0.006	2.5	0.012	110-115	0.002	0.0	0.363
115-120	0.009	3.6	0.000	120-125	0.015	24.0	0.000
125-130	0.010	4.9	0.000	130-135	0.004	1.7	0.080
135-140	0.002	1.0	0.30				

Table 13: Location Determinants of New Plants (Negative Binomial estimation)

	Food	Clothes	Wood	Printing	Chemistry	Other non met.	First transf. of metals	Machinery	Electronic equipment	Transport equipment
ACC	-.1682	-.1508	-.4462	-.1949	-.1714	-.0829	-.1692	-.1561	-.0633	-.0549
	(.0331)***	(.0307)***	(.0846)***	(.0829)**	(.0330)***	(.0214)***	(.0319)***	(.0269)***	(.0248)**	(.0242)
HC	4.0418	3.1745	2.8475	7.6746	3.7957	3.2099	-.9072	6.1012	8.1886	6.5839
	(1.0307)***	(1.0466)***	(1.0988)**	(.9498)***	(1.0143)***	(.8754)***	(1.4814)	(.9796)***	(.9965)***	(1.1331)***
GDP	-9.9900	-.0000	.0000	.0000	-.0000	-.0000	-.0000	-.0000	-8.4900	-.0000
	(.0000)	(.0000)	(.0000)**	(.0000)	(.0000)	(.0000)	(.0000)***	(.0000)	(.0000)	(.0000)
DI	.7149	1.3943	.8687	1.8303	.9451	1.3629	.7520	.9990	1.8861	1.4407
	(.3016)**	(.2758)***	(.2901)***	(.2116)***	(.2694)***	(.2585)***	(.3504)***	(.3012)***	(.2166)***	(.3406)***
LQ	.0246	.4624	.2393	.1660	.1217	.1257	.1295	.0867	.1252	.3701
	(.0225)	(.0292)***	(.0198)***	(.0414)***	(.0448)***	(.0203)***	(.0208)***	(.0513)*	(.0503)**	(.0604)
WLQ	-.1237	-.0007	2.8517	-2.0174	-.6164	-2.7829	3.8646	-1.4278	-.1575	
	(.0570)**	(.1633)	(.5182)***	(1.0452)**	(.6831)	(.9858)***	(.7682)***	(.2639)***	(.2287)	
WDI	8.7944	7.4696	-6.3412	.8170	8.8701	11.6447	3.2546	8.2218	2.9898	1.1895
	(1.2946)***	(1.3831)***	(1.7222)***	(1.0219)	(1.3424)***	(2.8189)***	(.5735)***	(1.0552)***	(.5955)***	(.6252)*
WHC	-36.0218	-26.6607	-73.1416	-26.3433	-24.2423	-17.2635		-3.6483	-7.6672	-9.2439
	(5.5166)***	(4.5171)***	(13.2692)***	(9.6158)***	(3.4966)***	(2.8874)***		(1.6129)**	(3.7756)**	(3.9518)**
WGDP	-.0638	-.0565	-.0407	-.0046	-.0617	-.0386	-.0687	-.0862	-.0024	-.0050
	(.0148)***	(.0140)***	(.0081)***	(.0030)	(.0144)***	(.0119)***	(.0162)***	(.0168)***	(.0029)	(.0129)
VHAT1	.1658	.1388	.4405	.1844	.1573	.0792	.1601	.1420	.0407	.0395
	(.0336)***	(.0308)***	(.0848)***	(.0830)**	(.0333)***	(.0217)***	(.0322)***	(.0270)***	(.0245)	(.0247)
Constant	10.0365	5.5307	34.8380	7.6470	4.9300	-.2722	.1873	.0754	-5.5056	-2.733
	(2.9704)***	(2.4817)**	(7.8498)***	(6.9105)	(2.3246)**	(1.3687)	(1.1428)	(1.6381)	(2.2124)	(2.3472)
Lnalpha	.8045	1.1272	.6353	.7993	.9301	.5898	.6660	1.1908	1.0280	.9949
	(.0634)	(.0718)	(.0589)	(.1035)	(.0727)	.0843	.0540	(.0891)	(.1387)	(.1535)
alpha	2.2357	3.0869	1.8876	2.2241	2.5348	1.8037	1.9464	3.2898	2.7954	2.7044
	(.1418)	(.2218)	(.1112)	(.2302)	(.1842)	.1520	.1051	.2931	(.3878)	.4152
Observations	7754	7754	7754	7754	7754	7754	7754	7754	7754	7754
Log Lik	-5944.8477	-3955.1961	-5885.7429	-2437.1098	-2837.4687	-3486.2893	-6263.143	-2747.7524	-1320.4307	-1631.327

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). *W* is a binary spatial weight matrix whose elements, w_{ij}, are set to 0 if municipalities *i* and *j* are far from a certain kilometric distance and to 1 otherwise (95 for Food, drinks and tobacco; 105 for Clothes and leather; 70 for Wood and furniture; 35 for Printing and paper; 105 for Chemistry; 145 for Other non metallic minerals; 90 for First transformation of metals; 55 for Machinery; 50 for Electric and electronic equipment; and 135 for Transport equipment).

Appendix I Correlations and basic summary statistics for some regression variables

	Variable	Mean	St. Dev.	Min	Max
Accessibility (minutes)	ACC	36.59	34.25	0	209.20
Human capital	HC	0.28	0.10	0	0.94
Diversity index	DI	0.63	0.43	0	4.20
Gross domestic product (mill €)	GDP	36.91	471.21	0	32798.61
Food, drinks and tobacco	LQ	2.10	11.72	0	723.00
	LOC	0.80	5.77	0	367.00
Clothes and leather	LQ	0.69	1.74	0	53.45
	LOC	0.58	5.19	0	238.00
Wood and Furniture	LQ	1.33	2.47	0	63.03
	LOC	0.85	6.78	0	494.00
Printing and paper	LQ	0.24	1.29	0	31.65
	LOC	0.32	3.68	0	261.00
Chemistry	LQ	0.26	1.45	0	58.36
	LOC	0.29	1.74	0	74.00
Other non metallic minerals	LQ	0.79	2.76	0	113.51
	LOC	0.28	1.26	0	37.00
First transformation of metals	LQ	1.09	3.28	0	163.86
	LOC	0.96	4.52	0	125.00
Machinery	LQ	0.78	7.32	0	601.72
	LOC	0.29	2.00	0	73.00
Electric & electronic equipment	LQ	0.21	2.71	0	185.87
	LOC	0.10	1.02	0	56.00
Transport equipment	LQ	0.12	0.70	0	10.87
	LOC	0.10	0.65	0	26.00

LQ: location quotient (1990); LOC: number of establishments created (1991-95)

Correlations

	ACC	HC	GDP	DI
ACC	1.000			
HC	-0.2501	1.000		
GDP	0.0009	-0.0075	1.000	
DI	-0.1848	0.3370	0.0007	1.000