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ACCESSIBILITY AND INDUSTRIAL LOCATION: EVIDENCE FROM SPAIN

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Accessibility and Industrial Location: Evidence from Spain*

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Abstract

This paper deals with location decisions of manufacturing firms in Spain. We analyse how agglomeration economies and, especially, transport accessibility influence location decisions of firms. During the 1990s there was an intense programme of high capacity road construction which improved accessibility to municipalities. We analyse 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 econometrics models) and some of the explanatory variables (local added value, road accessibility, and the characteristics of firms in neighbouring municipalities). The results show that agglomeration economies (including road network improvements) are important in industrial location decision-making.

Key words: accessibility, industrial location, spatial statistics and spatial econometrics,

Resumen

Este artículo trata de las decisiones de localización de las empresas manufactureras en España. Se analiza como las economías de aglomeración y, especialmente, la accesibilidad a la red de transporte afectan a las decisiones de localización. Durante la década de los 90 hubo en España un intenso programa de construcción de carreteras de alta capacidad que mejoró sustancialmente la accesibilidad de los municipios. El análisis de las decisiones de localización de las empresas se realiza a escala municipal y para tres ramas manufactureras. Las principales contribuciones empíricas de este artículo son las técnicas econométricas utilizadas (modelos econométricos espaciales) y algunas de las variables explicativas empleadas (valor añadido municipal, accesibilidad a la red de carreteras de alta capacidad, y las características de las empresas de los municipios vecinos). Los resultados muestran que las economías de aglomeración, al igual que las mejoras de accesibilidad, son importantes en el proceso de toma de decisiones de localización.

Palabras clave: accesibilidad, localización industrial, estadística espacial y econometría espacial

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1. Introduction

Traditionally, the location of economic activity has received little interest from scholars. Since the 1980s, however, several interesting papers on the interaction between space and economic activity have been published using different theoretical and methodological approaches such as New Economic Geography (Fujita et al., 1999) or Spatial Econometrics (Anselin, 1988), among others. By taking space into account, these contributions have been better able to analyze spatial interactions in econometric models.

This paper analyses how agglomeration economies act on firm location decisions at a local level in Spain. We also pay special attention to how accessibility[1] to the highway network (HN, hereafter) shapes those decisions. For this reason, we focus on the *Plan General de Infraestructuras* (General Infrastructure Plan: GIP) developed between 1984 and 1991 that extended the HN throughout Spain considerably. [2]

We assume that location patterns differ according to the specific characteristics of manufacturing industries. In order to better portray these differences, we have selected three manufacturing industries. Following OECD classification (OECD, 2001), these industries belong, respectively, to high-technology industries (computing, office equipment, and medical, surgical, precision, optical and watch making instruments and equipment), medium-technology industries (chemical industry: rubber, plastic and basic chemical products) and low-technology industries (food, drinks and tobacco). These industries account for around 25 % of the manufacturing employment and establishments in our sample (see Table 1).

This paper contributes to the extant literature by analysing a singular case in which road accessibility has considerably improved in a short period of time. This is of great interest for testing the effects of such improvements on the location decisions of manufacturing firms.

This paper is organised as follows: Section 2 reviews the literature on industrial location and road accessibility; Section 3 presents an explanatory spatial analysis; Section 4 provides our data, econometric specification and results; and Section 5 provides a short conclusion.

2. Determinants of the Location of Manufacturing Establishments

There is a wide range of recent contributions that analyse the location determinants of new firms, both from theoretical and empirical perspectives. Hayter (1997) summarises the latter by grouping them into three approaches: a neoclassical approach, a behavioural approach and an institutional approach. The neoclassical approach considers that location determinants are related to profit-maximising and cost-minimising strategies. The behavioural approach assumes that location decisions are taken under conditions of uncertainty and imperfect information, and, finally, the institutional approach focuses on the institutional environment in which location decisions are taken. According to the neoclassical approach, the main determinants can be proxied by variables such as agglomeration economies, land prices, wages, transportation costs and worker's skills, among others; the behavioural approach is based on firm size and non-economic variables such as the entrepreneur's personal circumstances; and finally, the institutional approach focuses on variables such as the characteristics of suppliers and customers, public policies and trade union strategies.

Most empirical contributions on industrial location determinants rely on the neoclassical approach and, specifically, on agglomeration economies.[3] In this paper we will focus our analysis on the impact of accessibility and, specifically, on the locational consequences of improvements in the highway network.[4]

Some scholars analyse how improvements to the road infrastructure affect productivity in the private sector that uses it (Garcia-Milà and García-Montalvo, 2007; Garcia-Milà and McGuire, 1992; Carlino and Mills, 1987; Carlino and Voith, 1992; Arauzo, 2005). Other scholars (Aschauer, 1989) study how all types of infrastructure affect job creation or productivity. Also, since the services provided by infrastructures are linked to their geographical position, the territories in which the infrastructures are located will enjoy comparative advantages. Some contributions, however, show that the consequences of improved accessibility are not the same for all industries and that it is necessary to analyse the specific characteristics and specific location requirements of each industry (Chandra and Thompson, 2000). It is possible, therefore, that spillovers generated by the HN will be both positive and negative (Boarnet, 1998), that is, some geographical areas will benefit while others will be harmed.

Besides these industry-specific components, we should point out that, although theoretical contributions emphasize the role of investment in infrastructure on economic growth, the empirical evidence (based on the characteristics of the territorial areas analyzed) provides contradictory results. Less favourable effects are observed, for example, in the non-metropolitan areas (mainly for transport infrastructure such as the HN). Specifically, a better HN may drive firms out to the (now) nearer metropolitan areas as a result of the lower transportation costs. Unfortunately, the effects of improved HN on firm relocation have received little attention in the literature (Boarnet, 1998).

Another way to analyze the impact of these infrastructures is from the perspective of agglomeration economies. The existence of agglomeration economies has traditionally been considered an important locational determinant, but at the same time improvements in the HN can erode these agglomeration economies (Haughwout, 1999). For example, these improvements make it easier to move merchandise and people between the centre and the periphery, making it less necessary to locate in the centre and decreasing the positive effects of the agglomeration. Specifically, it becomes easier (and cheaper) to produce commodities elsewhere and transport them to markets.

Regarding the industrial aspects, we can assume that different industries have different requirements in terms of the transportation demand of heavy inputs and outputs. This explains why proximity to the HN will not be the same for all industries (note that closer proximity implies also higher land prices). In any case, the positive effects incurred by being closer to the HN need to be clarified especially if transportation costs fall and non-material flows rise (Holl, 2004a). Because of such considerations, some scholars nowadays doubt whether transportation costs can be considered a locational factor. This is a very different position from that of mainstream economics since Weber's study (1929).

In this context, 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. This process has led to a deconcentration of economic activity as peripheral municipalities have increased their accessibility and more new firms have located there.

There is also empirical evidence from Spain regarding the impact of HN on the location decisions of firms (Holl, 2004a and Arauzo, 2005).[5] The main results agree with those of other countries: municipalities located near the HN increase their locational attractiveness in comparison with other municipalities, and this effect differs according to the manufacturing industry, since not all the manufacturing industries share the same accessibility requirements.

Previous arguments have shown that the effect of transportation costs (accessibility) on the spatial distribution of economic activity is neither clear nor obvious, since greater accessibility can lead to opposite effects on firm location (acting both as centrifugal and centripetal forces). In any case, it is important to conclude that investments in transport infrastructure influence the spatial distribution of economic activity so that some areas benefit (due to a greater capacity to attract firms) and others are harmed (due to the expulsion of firms towards those areas whose accessibility has increased) (Haughwout, 1999).

Despite previous comments regarding the bi-directional effects of accessibility improvements and local attractiveness for new firms, we assume that the better connected a municipality is to the HN, the more attractive it is for the location of new firms and for the endogenous growth of local firms.

3. Exploratory spatial analysis of the location of manufacturing establishments

In this paper we use municipalities as the spatial units, however this is not a trivial choice. Most authors think that location and spatial effects should be analysed at a local level and so European NUTs II and NUTs III should be rejected (Audretsch and Feldman, 1996; Ciccone and Hall, 1996; Viladecans, 2004), since these areas are so large. Theoretically, we cannot defend the superiority of municipalities over other territorial areas below European NUTs III, such as the Spanish *comarcas* or metropolitan areas. However, since there is no standard classification of Spanish municipalities into either *comarcas* or metropolitan areas, municipalities seem to be the best practical choice for the Spanish case.

For the exploratory analysis we studied whether the creation of new manufacturing units followed spatial patterns. To do so we applied Spatial Statistics Techniques and analyzed the period of time over which the General Infrastructure Plan (GIP) was carried out, as well as the subsequent period. We are not only interested in the existence of these spatial patterns, we also want to find out whether they have been affected by the improvements in accessibility.

3.1 Methodology

In this section we carry out an exploratory analysis in order to test whether the creation of new manufacturing establishments followed a spatial pattern during the GIP period and whether this pattern changed due to the greater accessibility derived from the GIP. This analysis consists of cartograms and spatial autocorrelation tests, such as Moran's I test and the BB Joint Count test. Since the GIP lasted from 1984 to 1991, we will analyse two periods: 1986–1990 and 1991–1995. Before carrying out the spatial exploratory analysis we have summarized the creation of new manufacturing establishments in Spanish municipalities[6] in Table 1. The data on new manufacturing establishments is taken from the Spanish Registry of Manufacturing Establishments (REI):[7]

[INSERT TABLE 1]

Table 1 shows that the location of manufacturing establishments[8] was slightly larger during 1986-1990 than during 1991-1995. The number of municipalities in which these establishments were located was also larger in the first period. Those differences could easily be explained by the fact that in the late eighties the Spanish economy was experiencing an important growth period.

As stated in the introduction, instead of analysing all manufacturing activities as a whole, we have decided to select three specific industries: computing, medical and precision instruments (high-technology), the chemical industry (medium-technology) and food, drinks and tobacco (low-technology). The reason is that they present some specificities in terms of technology, productivity, labour demand and markets, among others. These differences may also apply for location purposes, so we expect these industries to be influenced by different location determinants.

The exploratory analysis is shown in Figures 1 to 9. For each industry we first present the cartograms on the creation of establishments during both the 1986-1990 and the 1991-1995 periods, and on the industry specialisation in the municipalities in 1990.[9] 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, and the circles themselves are aligned as closely as possible to the original location of the matching spatial units by means of a nonlinear optimization routine (Anselin, 2005). The circles may be highlighted in white (zero value), in green (around the medium value), or in red (upper value). On the one hand these cartograms show where the new establishments were located (Figures 2, 5 and 8), and how important these municipalities are as a location for each industry. The latter can be also shown in the cartograms for the industry specialisation (Figures 1, 4 and 7), which is measured by the location quotient, defined as follows:

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

where E_{im} represents total employment in manufacturing activity *m* in the municipality *i*, E_i represents total employment in the 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.[10] Comparison of birth cartograms with location quotient cartograms tell us whether the more specialised municipalities are also the ones in which more births are located.

After presenting the cartograms we show the spatial autocorrelation statistics, both global and local Moran's I on the location quotient, and the BB Joint Count test on the births (Tables 2, 3 and 4). Global Moran's I indicates whether there is positive spatial autocorrelation. That is, it indicates whether positive and significant z-values for this statistic, that is, either low or high values, are more spatially clustered than could be caused purely by chance (Anselin, 1992). Therefore, if there is positive spatial autocorrelation in the industry specialisation of the municipalities, most of these municipalities should be neighbours. Global Moran's I statistic is defined as follows:

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

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* are neighbours that is, if they share a common border; it is set to 0 otherwise); x_i and x_j are observations for locations *i* and *j* (with mean u), and *So* is a scaling constant: ($So = \sum_i \sum_j w_{ij}$).

In order to see whether the industry specialisation of a given municipality follows a spatial pattern we use cluster maps (Figures 3, 6 and 9), which show those locations with a significant Local Moran statistic classified by type of spatial autocorrelation:

bright red for high-high association; bright blue for low-low association; light blue for low-high association; and light red for high-low association. The high-high and low-low location suggest clustering of similar values (positive spatial autocorrelation), whereas the high-low and low-high locations indicate spatial outliers (Anselin, 2003).

Finally, we present the BB Joint Count test on the creation of new establishments. This test shows whether binary variables are clustered or randomly distributed in space. This test is defined as follows (Cliff and Ord, 1980):

$$BB = (1/2)\sum_i \sum_j w_{ij} x_i x_j \,, \tag{3}$$

where w_{ij} is the i-j_{th} element of a spatial weights matrix (W) and x is a binary variable. A positive and significant z-value for this statistic indicates positive autocorrelation, that is, similar values, whether high or low, are more spatially clustered than would be possible if they were caused purely by chance (Anselin, 1992).

Significant and positive z-values for the spatial autocorrelation statistics show agglomerative behaviour. This behaviour may be caused by external economies, such as location or urbanization economies and, according to the so called New Economic Geography, it also may be caused by low transport costs, that is, by better accessibility (Fujita et al, 1999).

3.2 Results

A cartogram for the food location quotient is shown in Figure 1. Manufacturing of food products seems to be widely distributed across Spanish municipalities, except for some areas in the southern provinces. However, apart from the Madrid area, the creation of new establishments focuses on the periphery and, above all, the Mediterranean coast (Figures 2a and 2b), both in the first and in the second period. It should be stressed that many establishments are created in highly dynamic economic areas, such as Barcelona or Madrid, which are not specialized in the food industry.

[INSERT FIGURES 1 AND 2]

Local Moran's I map for the location quotient of the food manufacturing industry (Figure 3) shows that some areas (coloured in red) are specialised in the food industry, which means that there is a positive spatial autocorrelation. However, it also shows that there is negative spatial autocorrelation in some areas (municipalities highlighted in light blue) as well as low-high association (municipalities highlighted in light red). These results are consistent with global Moran's I for the location quotient (Table 2.1), which shows that evidence on global positive spatial autocorrelation for food specialisation is weak, since the statistic is only statistically significant in the permutation approach, is weakly significant in the randomization assumption, and is not significant in the normal approach.

[INSERT FIGURE 3]
[INSERT TABLE 2]

However, according to the BB joint count test statistic (Table 2.2), the creation of new food manufacturing establishments is highly and positively spatially autocorrelated. That means that the creation of establishments from the food manufacturing industry in every municipality is related to the creation of new establishments of the same industry in neighbouring municipalities, which may reflect the existence of interurban externalities and should be taken into account in the confirmatory analysis.

[INSERT FIGURE 4]

As can be seen in Figure 4, chemistry manufacturing establishments are much more spatially concentrated than food manufacturing establishments. The Basque Country, Catalonia, Cantabria, Valencia and Madrid are the most specialised areas. Catalonia, Madrid and Valencia are also the areas which received more new establishments (Figure 5) and, according to the local Moran's I statistic, Catalonia and Madrid are the ones which show a highly significant agglomerative pattern (Figure 6).

[INSERT FIGURES 5 AND 6]

Global Moran's I statistic on specialisation in chemistry is also significant and positive (Table 3.1). Finally, the births BB joint count statistic test for the new establishments (Table 3.2), again shows empirical evidence of positive spatial autocorrelation, which may be caused by spatial externalities.

[INSERT TABLE 3]

Results for the computer and office equipment industry are very similar to those of the chemical industry. Both the Catalonia and Madrid areas are more specialised (Figure 7), receive more new establishments (Figure 8a and 8b), and show a higher, positive and significant agglomerative pattern (Figure 9).

[INSERT FIGURE 7, 8 AND 9]

Both Global Moran's I statistic (Table 4.1) and the BB joint count test for spatial autocorrelation (Table 4.2) confirm this spatial pattern.

[INSERT TABLE 4]

Our results show that there are no significant differences in the spatial patterns between both periods. A possible explanation for those similarities could be that decision makers anticipated future improvements in accessibility when they decided the location of their new establishments. In any case, even if the highway network has been considerably improved during the period analysed, it is not clear if that period (10 years) is long enough to capture important changes in location patterns since there is clearly path dependence in this type of phenomenon.

4. Data, model and results

Investments in the road network used to be greater in areas with a greater concentration of economic activity and a greater capacity to attract new firms. [11] It is necessary, therefore, to control these non-observable locational characteristics that also influence the extension of the road network and the location of firms. It is also important to analyse whether the construction of new transport infrastructure is an exogenous variable and thus not related to previous economic growth in this area.[12] In this context, Chandra and Thompson (2000) show that the location decisions for this infrastructure 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 total 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.

4.1 Variables and data

We can only make estimations for the second period (1991-1995) because of lack of data for the first period (1986-1990). As a dependent variable, we use LOC_{im}, which reflects the creation of manufacturing establishments in municipality *i* and in manufacturing industry *m* over the period 1991-1995. As we will show in sections 4.2 and 4.3, LOC_{im} will account for the number of new manufacturing establishments in Poisson and binomial negative models. However, in spatial Probit models LOC_{im} will be set to 1 if at least one establishment of manufacturing industry *m* has been located in municipality *i* over the period, otherwise it will be set to 0.

Following the neoclassical approach (Hayter, 1997), location determinants are usually grouped into categories such as supply factors, demand factors and external economies and diseconomies (Guimarães *et al*, 2004). Accessibility may be considered as a supply factor since it means lower transport costs, but it may also enlarge the geographical extent of externalities. Besides accessibility, the location factors we take into consideration are: human capital (supply side); internal market (demand side); external economies related to urban agglomeration and external economies related to local specialisation as spatial externalities. Finally, we consider the interurban agglomeration forces, that is, the human capital, the internal market, and the spatial externalities of the neighbouring municipalities,[13] since the decision of locating a manufacturing establishment in a given municipality may be also influenced by the characteristics of the surrounding municipalities. To sum up, the creation of new manufacturing establishments can be expressed as follows:

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

where ACC_i is the accessibility indicator for municipality i and reflects the time needed to access the highway network from municipality i. It is constructed using Geographical Information Systems[14] and, since better accessibility means less travelling time, its sign is expected to be negative.

The human capital index (HC_i), is defined as the percentage of the population with at least one secondary school degree in municipality *i* in 1991. We think, *ceteris paribus,* that decision makers prefer locations with a more qualified labour market to locations with a less qualified labour market, even if this implies higher wages. Human capital is therefore expected to be positively related to location decisions. The HC_i data is taken from the 1991 Spanish Population Census (*Censo de Población 1991*).

Internal market is measured by LVA_i, which is the local value added of municipality i taken from Alañón (2002). Local value added reflects both local economic activity and the internal potential market of the municipality. Its sign 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). Usually, 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-trade local inputs, etc. According to Duranton and Puga (2000), not only is the creation of new plants biased towards larger and more diverse cities, but the location of innovative activities that lead to new products is also biased. 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:

$$DI_i = 1/\sum_m / s_{im} - s_m / \ , \qquad (5)$$

where s_{ij} 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.[15] LQ_{im} measures the relative specialisation of municipality i in industry m and is the location quotient defined in expression 1. Its sign is expected to be positive. Since higher LQ_{ij} may be caused by a large number of small firms or by a small number of large firms, it may also reflect the effects 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 potential role of interurban agglomeration forces (IAF_i).These interterritorial externalities are usually restricted to interregional contexts.

However, some authors have applied this concept to a less aggregated spatial scale both implicitly, as in Ellison and Glaeser (1997), and explicitly, as in Alañón (2004) and Alañón and Myro (2005). As tested in Alañón and Myro (2005), interurban agglomeration forces played an important role in the location of manufacturing establishments in Spanish peninsular municipalities over the period 1991-1995. Broadly speaking, 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).

As will be shown in the next section, the IAF_i indicator will depend on the kind of model estimated. In count models (the Poisson and Negative Binomial models) we will use the spatially lagged independent variables, WHC_i, WLQ_i, WDI_i and $WLVA_i$, where W is a contiguity matrix. In the spatial probit models we will use the autoregressive variables λWu for the spatial error model, and ρWy for the spatial autoregressive model, where W is a contiguity matrix, u is the error term, y is the dependent variable and λ and ρ are parameters.

4.2 Econometric specification

Most recent contributions in location analysis use count data models in order to model the location decisions of new firms.[16] These models have some advantages related to the typical nature of location data and with the spatial level in which the analysis is conducted (usually at local level). That is, they can deal with the "zero problem",[17] the situation in which a large number of territorial units receive no new establishments (which is typical when the territorial units are so small, as municipalities are, for instance).

In this context, the dependent variable in count data models is the number of firms located in each territorial unit (municipality). According to this approach, 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 that a municipality will attract a firm depends on the specific attributes of the municipality:

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

where λ_i 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 to where a firm locates but also on the characteristics of neighbouring municipalities.

Additionally, the Poisson model 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 Poisson model (the Negative Binomial model) 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 with exp (ε_i) having a gamma distribution with mean 1 and variance α.

According to typical data used 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 a Negative Binomial model, which allows the variance to exceed the mean. In the Negative Binomial model the variance equals:

$$\mathrm{var}[y_i|x_i] = E[y_i|x_i]\{1+\alpha E[y_i|x_i]\} \tag{10}$$

If α equals zero, the conditional variance is equal to the conditional mean and the Poisson and Negative Binomial models are the same.

Location processes can also be analysed and estimated using binary discrete choice models, such us Probit models. Then, the dependent variable (*LOC*) would be set to 1 if the decision of setting up at least one manufacturing establishment in a municipality has been implemented, and to 0 if this is not the case. Formally:

$$Prob(LOC=1/X) \equiv G(XB) \equiv Prob(X) \quad , \tag{11}$$

where $G(z) \equiv \Phi(z) \equiv \int_{-\infty}^{LOC} \phi(v)dv$, and $\Phi(z)$ is the standard normal density. The main drawback of binary discrete choice models is that they do not use all the information available because *LOC* is set to 1 if there are new births, irrespective of the number of establishments that have been set up.

However, neither Negative Binomial models nor Poisson models account for the existence of spatial autocorrelation. As there is univariate spatial dependence in LOC_{im} (as shown in the exploratory analysis), and we are making LOC_{im} depend on what happens in neighbouring municipalities, the assumption of an independently distributed ε_{ij} is too strong. Since the existence of spatial autocorrelation invalidates most of the usual statistics and econometric techniques, and despite the strengths of the random profit maximization framework, we estimated spatial Probit models, the so-called Spatial Autoregressive Models (SAR) and the so-called Spatial Error Models (SEM).

SAR models include a spatially lagged dependent variable (*Wy*) as one of the explanatory variables. That is:

$$y = \rho Wy + X\beta + \varepsilon \,, \tag{12}$$

where y is a nx1 vector of observations on the dependent variable, Wy is an nx1 vector of spatial lags for the dependent variable, ρ is the spatial autoregressive coefficient, X is an nxk matrix of observations on the (exogenous) explanatory variables with an associated β kx1 vector of regression coefficients, and ε is an nx1 vector of normally distributed random error terms, with means 0 and constant (homoskedastic) variances σ^2.

SEM models deal with spatial dependence through a spatially lagged error term. That is:

$$
\begin{aligned}
& y = X\beta + u \\
& \quad u = \lambda W u + \varepsilon \\
& \quad \varepsilon \approx N(0, \sigma^2 I_n)
\end{aligned}
\tag{13}
$$

where λ is a coefficient on the spatially correlated errors.

Both spatially lagged dependent variables in SAR models and spatially lagged error terms in SEM models reflect the existence of spatial autocorrelation and both may be interpreted as a way of treating spatial dependence properly. However, they may also have an economic meaning. This can be clearly shown in the SAR models, in equation 12, and in its reduced form, equation 14, since it makes what happens in a given location depend on what happens in the neighbouring locations:

$$
y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon \tag{14}
$$

In the presence of spatial autocorrelation, standard Logit, Poisson and Probit models are discarded since ε does not follow a normal distribution in limited dependent models. So, the resulting multivariate specification is intractable in Logit and in standard Poisson[18] models, and standard Probit estimation is inconsistent (Anselin, 2002, p. 8). Despite the strengths of the random profit maximization framework, we are forced to ignore it because it does not deal with spatial autocorrelation, meaning that we must to consider spatial Probit models (both error and lag) as a feasible option for estimating location models.

Following Anselin (2001) and Fleming (2004) there are several ways of implementing spatial Probit models. These include generalized methods of moments (GMM) and estimation for error models (Pinkse and Slade, 1988); the EM (expectation, maximization) approach for error models (McMillen, 1995); and simulation estimators such as the Gibbs Sampler (Lesage, 1997 and 2000; Smith and Lesage, 2002). We have chosen the Gibbs Sampling approach to estimate the Bayesian Probit models proposed in Lesage (1997 and 2000) and Smith and Lesage (2002), since “it is the most flexible of the spatially dependent models because it can incorporate spatial lag dependence and spatial error dependence in addition to general heteroskedasticity, of unknown form” (Fleming, 2004, p.166-167).

As well as spatial Probit models, we estimated Negative Binomial models and Poisson models with spatially lagged explanatory variables. Although they may not treat spatial autocorrelation properly, the spatially lagged explanatory variables may help to explain the economic causes of spatial autocorrelation. Besides, unlike the spatial Probit models, Negative Binomial models and Poisson models take into consideration all the establishments created over a period of time.

4.3 Results

The results of our estimations are summarized in Tables 5, 6 and 7.[20] First of all, we should stress that the accessibility coefficient is significant and shows the expected sign in most of the econometric specifications. This greater accessibility influences firm’s location, as other empirical research has found in Portugal (Holl, 2004b), Spain (Holl, 2004a) and Catalonia (Arauzo, 2005).

[INSERT TABLE 5]

The role of accessibility in the food industry is not clear cut (Table 5) since the coefficient is not statistically significant in either Negative Binomial or SAR models. This could be partly due to the fact that the spatial pattern of this industry is highly dispersed (Figure 1, 2a and 2b). However the statistical significance of this coefficient is high both in the Poisson and in SEM models. In any case, the accessibility variable presents the expected negative coefficient in all the estimations. That is, when the time needed 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, as in those of Holl (2004a, 2004b), List (2001) and Coughlin and Segev (2000), among others.

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. Specifically, new establishments are positively attracted by skilled labour, weight of local economy (internal market), industrial diversity and local specialisation[21]. Empirical evidence on the previous internal characteristics of municipalities is not as clear as it is for accessibility. Human capital, for instance, is one of the most controversial location determinants since scholars have found both a positive and a negative effect on location decisions. Empirical industrial location literature has found that while firms prefer to be located in areas with good accessibility to educated workers (Coughlin and Segev, 2000; Woodward, 1992), there is also a negative effect of higher wage areas (i.e. areas with a high rate of skilled labour) on new firm entries (List, 2001; Friedman et al., 1992; Papke, 1991). Diversity is another local characteristic for which the effect is not clear in terms of locational determinants. Although it has been said that a specialised environment is preferred in order to benefit scale economies (Henderson et al., 1995), other authors argue that the greater the diversity of activities at a site, the greater the potential growth of this site (Glaeser et al., 1992; Jacobs, 1969).

Interurban agglomeration forces also seem to play a role in the location of new births, since the spatial autoregressive coefficients of the Spatial Probit models (both SEM and SAR) and almost all the spatially lagged explanatory variables are statistically significant in Negative Binomial and in Poisson models.

The internal market (WLVA) and the diversity of the neighbouring municipalities' (WDI) coefficient show the expected sign and are statistically significant for the food industry. However, the specialisation of neighbouring municipalities (WLQ) only seems to matter in the Poisson model. Finally, the human capital of neighbouring municipalities (WHC) is significant but shows a negative sign, which means that if a municipality is surrounded by other municipalities with high skill levels among the population, this situation has a negative influence on firm entries.

[INSERT TABLE 6]

In the chemical industry (Table 6), the accessibility coefficient (ACC) is significant and shows the expected (negative) sign in all model specifications. The other variables (HC, LVA, DI, and LQ) are also significant and all of them have a more positive effect on firm entries than for food industry. The role of interurban agglomeration forces (IAF) is also significant and positive in SEM and SAR models. Only the IAF derived from diversity (WDI) and from specialization (WLQ) are significant and present the expected sign in Poisson and Negative Binomial models, while IAF about local added value (WLVA) shows a significant (negative) coefficient only in the Poisson model and the human capital of neighbouring municipalities (WHC) is not significant.

[INSERT TABLE 7]

Results from the computer and office equipment industry (Table 7) are quite similar to those of the chemical industry, since ACC, HC, LVA, DI, LQ, WDI and WLQ are significant and show the expected positive sign in all the models estimated. However, neither λWe nor ρWLOC are significant. The reason for this lack of statistical significance is not clear, since spatially lagged coefficients for diversity (WDI), specialisation (WLQ) and human capital (WHC) in the Poisson and Negative binomial models, and the spatial autocorrelation statistics (Table 4) are significant. It could be due to the fact this industry's establishments are located in a few municipalities (Table 1): specifically, only 2.2% of the municipalities included in our sample received start-ups from computing, and medical and precision instruments in the 1991-1995 period.

To sum up previous results, 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. Policy implications of these results are clear, since municipalities are interested in diminishing travel time to such infrastructures. The other internal characteristics of the municipalities that have been taken into account (human capital, local value added, industrial diversity and specialisation) also show (mainly) a positive effect on location decisions, whatever the specific industry of entering firms.

Main differences among industries arise among spatial lags in those internal characteristics, which show interesting differences both in terms of signs and significance of coefficients. WDI has the same positive and significant coefficient for the three industries and count data specifications, but WHC, WLVA and WLQ behave in a different way.

WHC shows a significant and negative effect for high-tech (computing, medical and precision instruments) and low-tech industries (food, drinks and tobacco). This result is not an easy one to understand from a theoretical point of view, since it means that the higher the levels of human capital of neighbouring municipalities, the lower the entries.

These negative signs could be due to the fact that the information related to neighbouring human capital level may also be measured by neighbouring specialisation, so WHC indicators would be redundant. In any case, we must take into account industry specificities when interpreting these results, since it is possible that there is a spatial pattern for high-tech activities in which they are spatially isolated in a few municipalities, whereas low-tech activities (spread all over the country) try to avoid areas with higher levels of skilled labour in order to get better access to cheap labour.

Local value added in neighbouring municipalities (WLVA) only seems to be relevant for new entries in low-tech industries, where the indicator is significant and presents a positive sign. However it is not significant for high-tech industries, and its effect on medium-tech industries is not conclusive. These results are consistent both with the spatial exploratory analysis and with the industrial location literature (McCann, 2001). Proximity to the market is an important location factor for low added value industries such as the food industry, which is widely distributed across Spain (figures 1 and 2). Meanwhile, medium and high added value activities are less dependant on proximity to the market because their high added value/weight ratio allows them to be transported across long distances. These industrial activities are also more spatially concentrated (Figures 4, 5, 7 and 8) because, for example, the chemical industry's location may depend on natural advantages, whereas the computer industry's location may depend on scale economies, local know-how or other spatial externalities.

Finally, given that one could expect some different results for the manufacturing industries we have analyzed, their specific location patterns need to be analyzed in greater depth.

5. Conclusions

The aim of this article was to evaluate how improved access to the HN resulting from the General Infrastructure Plan (GIP) affected the creation of new manufacturing establishments in three different industries: computing, medical and precision instruments, food, drinks and tobacco and the chemical industry. Analysis shows that the location of each industry follows an agglomerative spatial behaviour (even though they share some common patterns), and suggests that decision makers anticipate these improvements in accessibility.

As our estimation results show, this agglomerative behaviour may be due both to interurban agglomeration forces and to improved accessibility. Results for the geographical scope of externalities are in line with other analyses (see Rosenthal and Strange, 2003; or Viladecans 2004, for instance). Poisson and Negative Binomial estimations with spatially lagged explanatory variables show that the source of these interurban externalities may be manufacturing specialisation and manufacturing diversity. As stated before, our analysis of location determinants is not comprehensive, thus this agglomerative behaviour may be also due to natural advantages (Ellison and Glaeser, 1997) or to history (Krugman, 1993).

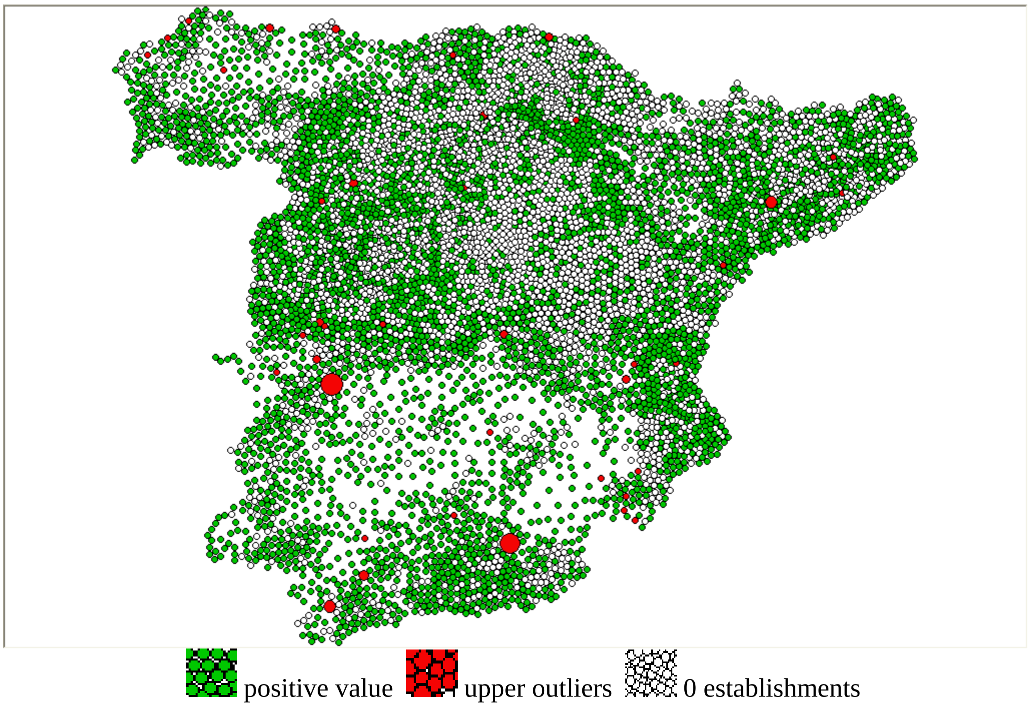
This agglomerative spatial pattern and the results for accessibility are consistent with the predictions of New Economic Geography because greater accessibility means lower travel costs and makes external scale economies more feasible, thus favouring agglomeration.

Despite these positive effects, we must bear in mind that investment in the infrastructure could have opposite territorial effects. On one hand, extending the HN may increase the accessibility of nearby municipalities, thus making them more attractive potential locations. On the other hand, 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 HN. Others may leave well-located large agglomerations in order to avoid negative externalities, such us congestion or higher land prices. The negative effects on distant municipalities may be even worse. Paradoxically, assuming that a substantive proportion of HN extension is funded by the Government, as in the Spanish case, this would mean that distant municipalities were funding infrastructures that encourage firms to migrate from these municipalities (Boarnet, 1998) or which make these municipalities a less attractive potential location for new firms. Any empirical approach to the causal relationship between accessibility and firm location should therefore also consider these negative effects. Unfortunately, Spanish databases on manufacturing establishments do not collect information on firm relocations, so we can only focus on the overall effects on firm creation. Nevertheless, an important policy implication that arises from these results is that public decisions regarding improvements to high capacity roads should take into account the indirect effects resulting from increased accessibility to these roads.

6. Tables and figures

Table 1 Creation of new manufacturing establishments 1986-1990 and 1991-1995						
	Employees 1990	Stock of Establ.1990	1986-1990		1991-1995	
			New Estab.	Municip.	New Estab.	Municip.
Food and tobacco	355456	36817	6853	2070	6323	1749
(% Manufacturing)	15,38	19,31	31,08		33,17	
Chemistry	213981	8484	3159	909	2278	795
(% Manufacturing)	9,22	4,45	14,33		11,95	
Computer, office equip. etc	33383	2539	629	216	440	177
(% Manufacturing)	1,43	1,33	2,85		2,31	
Estab = Establishments; Municip. = Municipalities. Source: REI and Censo de Locales 1990						

Figure 1: Food location quotient 1990 cartogram



Figures 2a and 2b: Cartograms for new food establishments: 1986-90, 1991-95

Figure 2a: 1986-1990

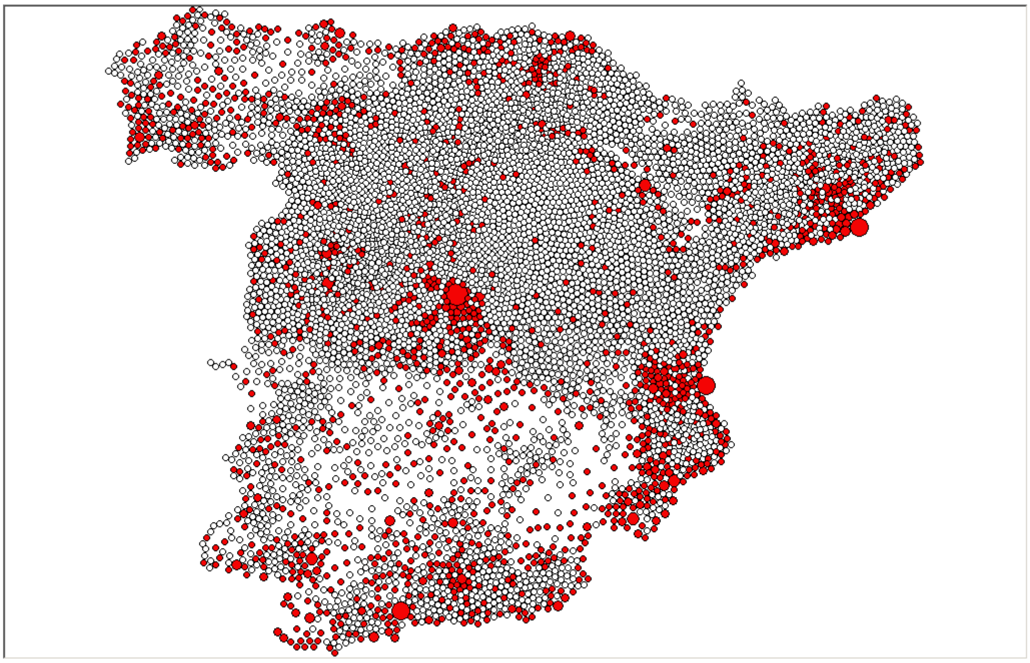
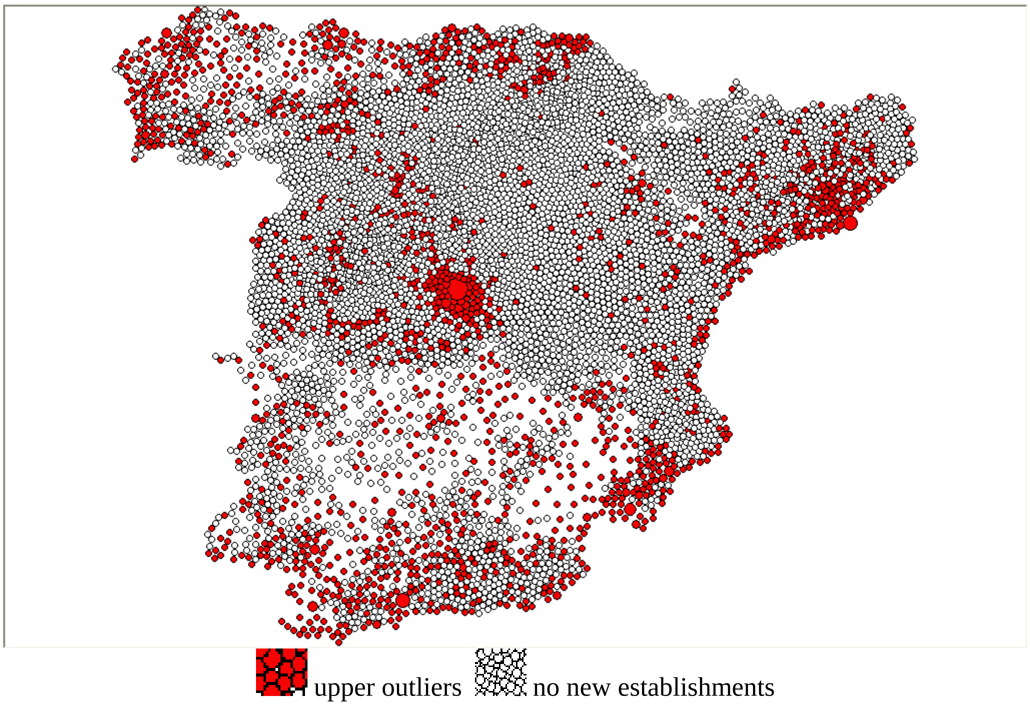
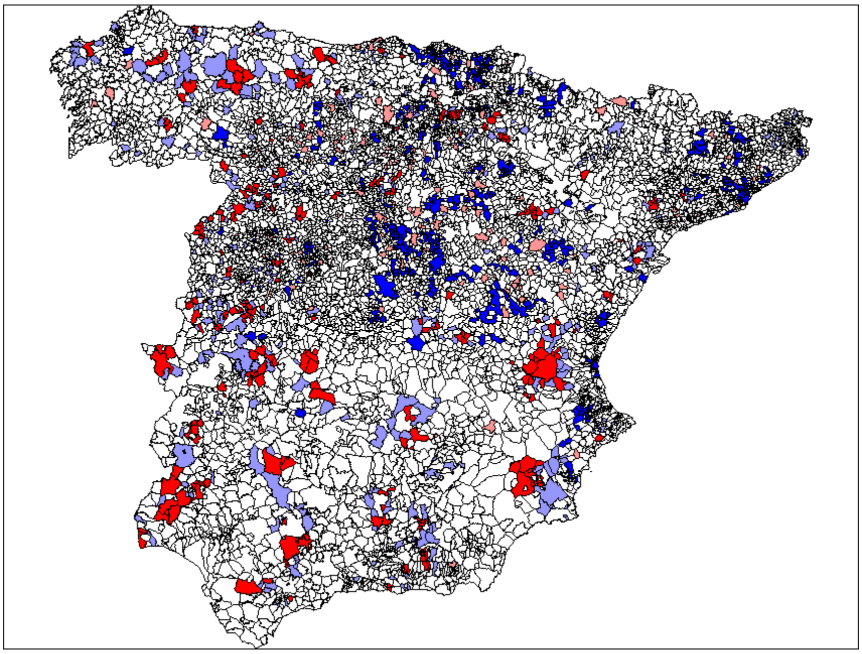


Figure 2b: 1991-1995



upper outliers no new establishments

Figure 3: Local Moran's I map for specialisation in food manufacturing industry



Spatial association				
Not significant		☐		
Positive	high-high	■	low-low	■
Negative	low-high	■	low-high	■

Table 2: Spatial autocorrelation statistics: food industry

Table 2.1 Moran's I test

a) Normal approach

Variable	I	Mean	St.Dev.	Z-Value	Prob
LQ	0.009110904	-0.000	0.006759	1.366760	0.171701

b) Empirical pseudo-significance based on 99 random permutations

Variable	I	Mean	St.Dev.	Prob
LQ	0.009110904	-0.001	0.002646	0.030000

c) Randomization assumption)

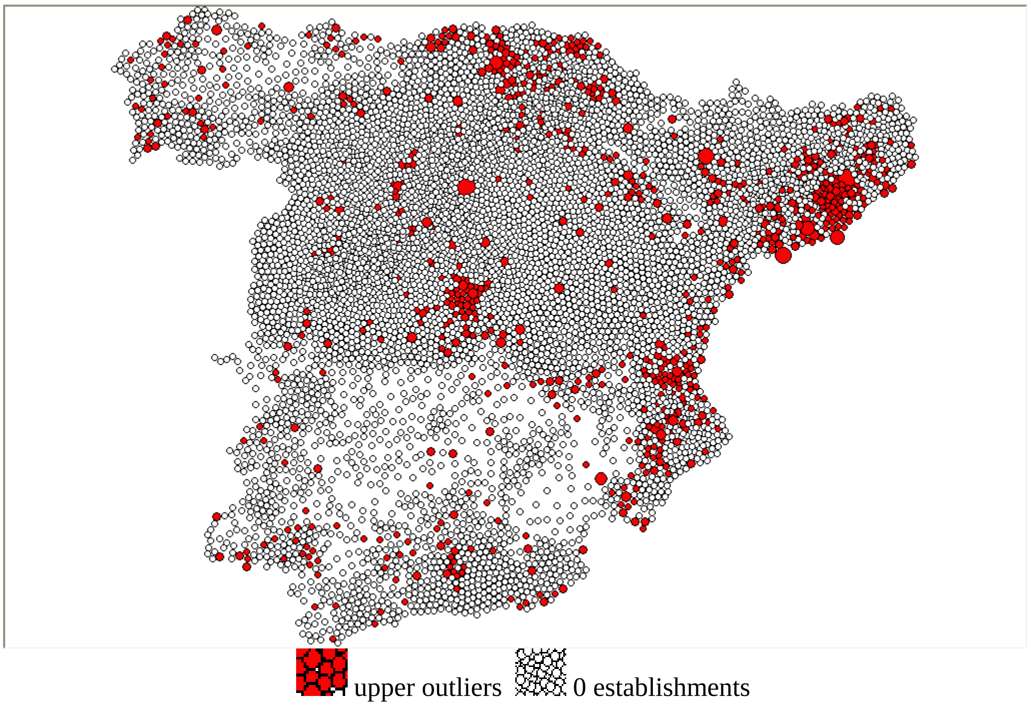
Variable	I	Mean	St.Dev.	Z-Value	Prob
LQ	0.009110904	-0.000	0.005353	1.725645	0.084411

Table 2.2 BB Joint Count test

Variable	BB	Mean	St.Dev.	Z-Value	Prob
LOC_{86}	597	218.254	14.683678	25.793	0.000000
LOC_{87}	684	225.769	14.931701	30.688	0.000000
LOC_{88}	649	209.740	14.397340	30.509	0.000000
LOC_{89}	660	198.652	14.015297	32.917	0.000000
LOC_{90}	543	173.780	13.116367	28.149	0.000000
LOC_{91}	555	169.712	12.963205	29.721	0.000000
LOC_{92}	492	125.524	11.160455	32.837	0.000000
LOC_{93}	477	135.721	11.602062	29.415	0.000000
LOC_{94}	570	158.774	12.541790	32.788	0.000000
LOC_{95}	622	166.693	12.848306	35.437	0.000000

LQ = Location quotient; LOC = Creation of manufacturing establishments

Figure 4: Chemistry location quotient 1990 cartogram



Figures 5a and 5b: Cartograms for new chemistry establishments: 1986-90, 1991-95

Figure 5a: 1986-1990

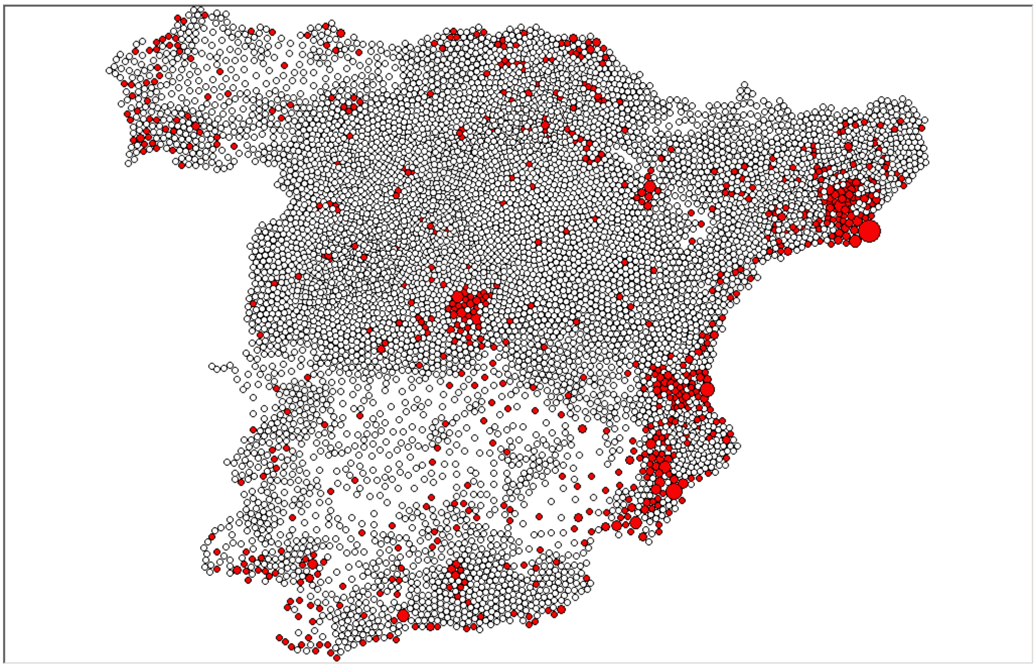
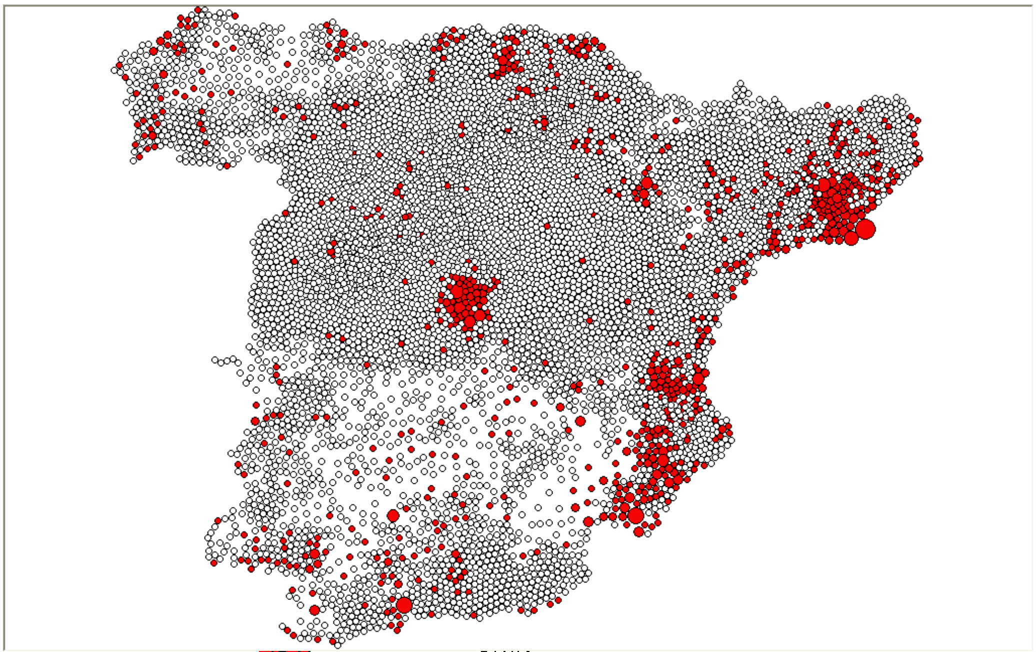
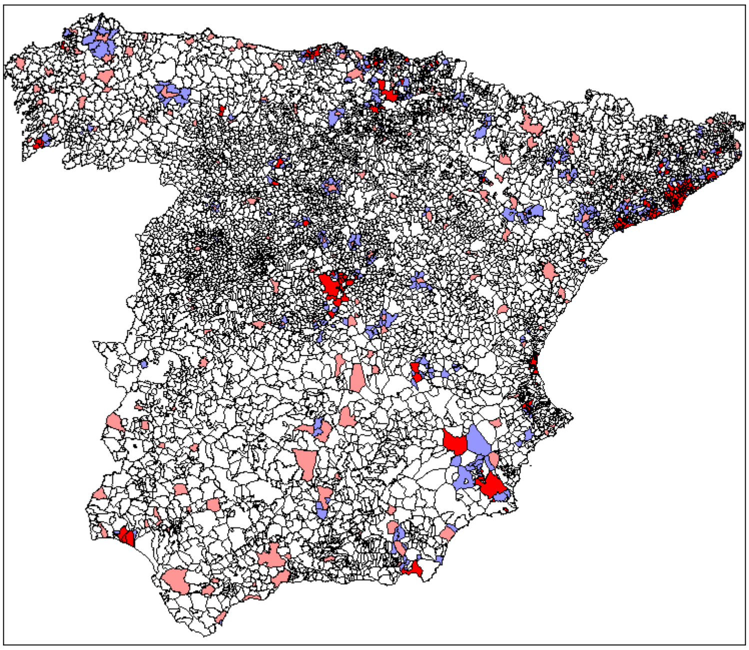


Figure 5b: 1991-1995



upper outliers no new establishments

Figure 6: Local Moran's I map for specialisation in chemical manufacturing industry



Spatial association				
Not significant		☐		
Positive	high-high	■	low-low	■
Negative	low-high	■	low-high	■

Table 3: Spatial autocorrelation statistics: chemistry

Table 2.1 Moran's I test

a) Normal approach

Variable	I	Mean	St.Dev.	Z-Value	Prob
LQ	0.07327209	-0.000	0.006759	10.860151	0.000000

b) Empirical pseudo-significance based on 99 random permutations

Variable	I	Mean	St.Dev.	Prob
LQ	0.07327209	0.000	0.007207	0.010000

c) Randomization assumption)

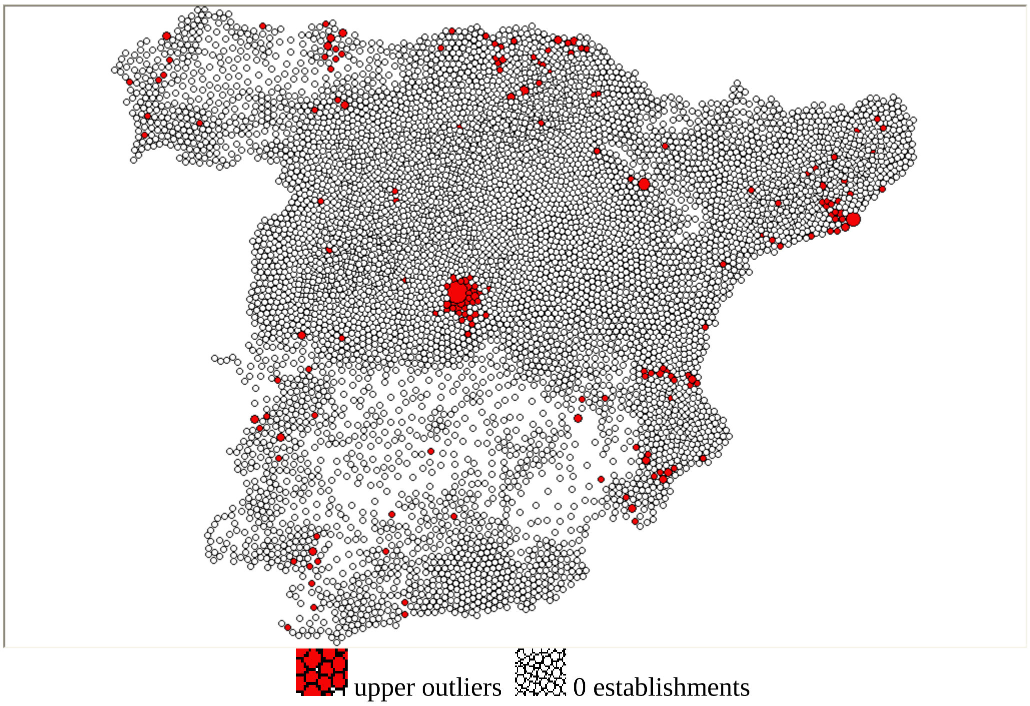
Variable	I	Mean	St.Dev.	Z-Value	Prob
LQ	0.07327209	-0.000	0.006542	11.220069	0.000000

Table 2.2 BB Joint Count test

Variable	BB	Mean	St.Dev.	Z-Value	Prob
LOC_{86}	229	37.464574	6.110825	31.343630	0.000000
LOC_{87}	271	46.767109	6.825761	32.850973	0.000000
LOC_{88}	264	37.702444	6.130154	36.915478	0.000000
LOC_{89}	267	45.188584	6.709860	33.057535	0.000000
LOC_{90}	231	41.610743	6.439371	29.411144	0.000000
LOC_{91}	239	39.145474	6.246121	31.996584	0.000000
LOC_{92}	243	33.986849	5.820848	35.907681	0.000000
LOC_{93}	187	26.731052	5.163295	31.040054	0.000000
LOC_{94}	165	18.465812	4.292473	34.137473	0.000000
LOC_{95}	211	30.037148	5.472777	33.066000	0.000000

LQ = Location quotient; LOC = Creation of manufacturing establishments

Figure 7: Computer and office equipment industry location quotient 1990 cartogram



Figures 8a and 8b: Cartograms for new computer and office equipment establishments: 1986-90, 1991-95

Figure 8a: 1986-1990

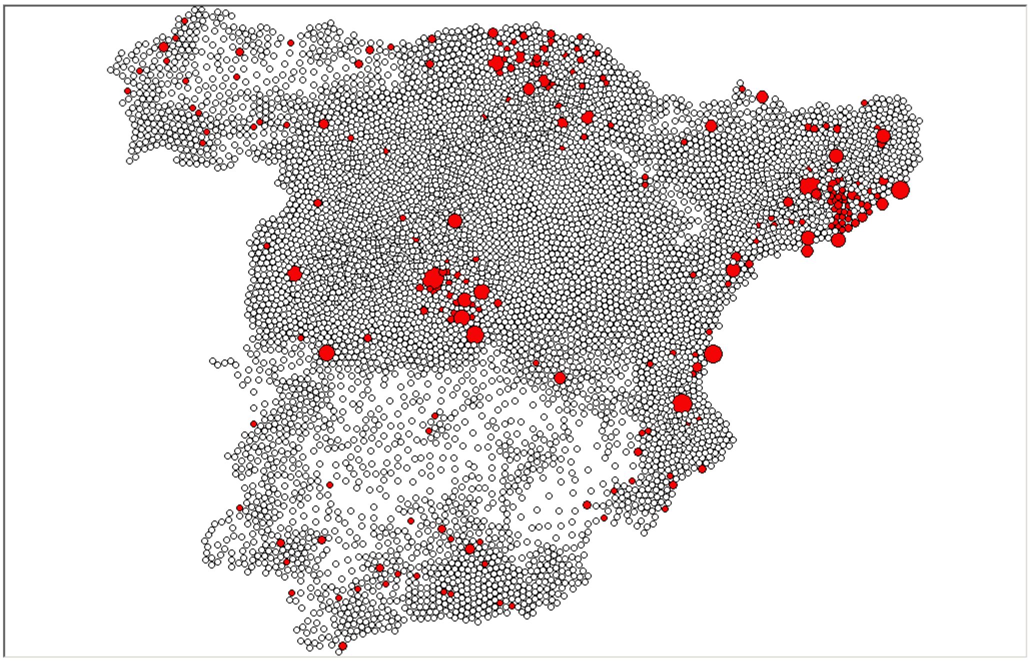
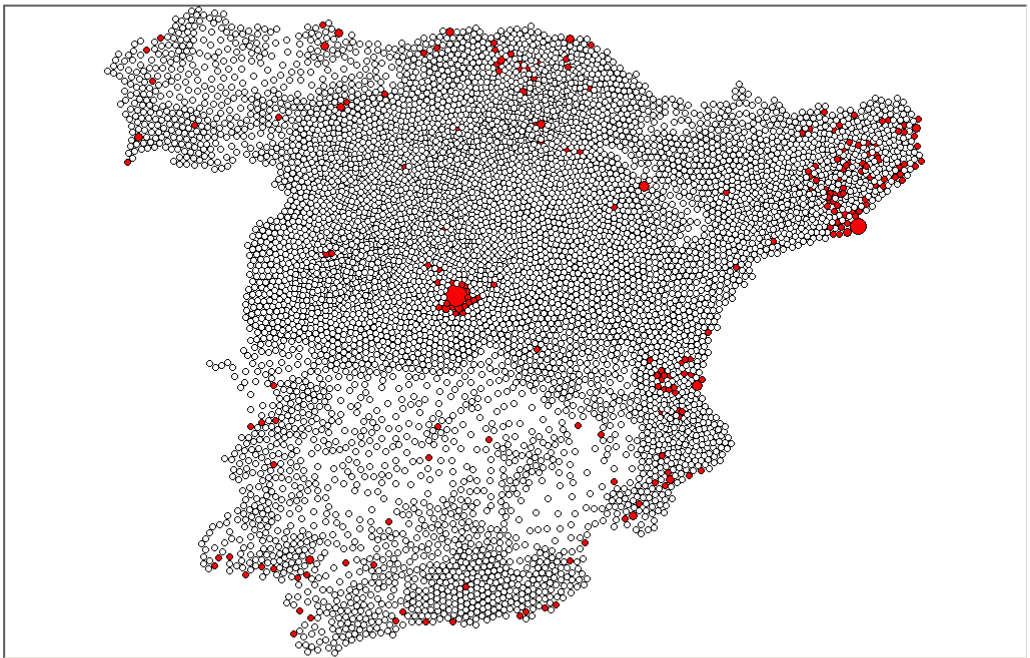
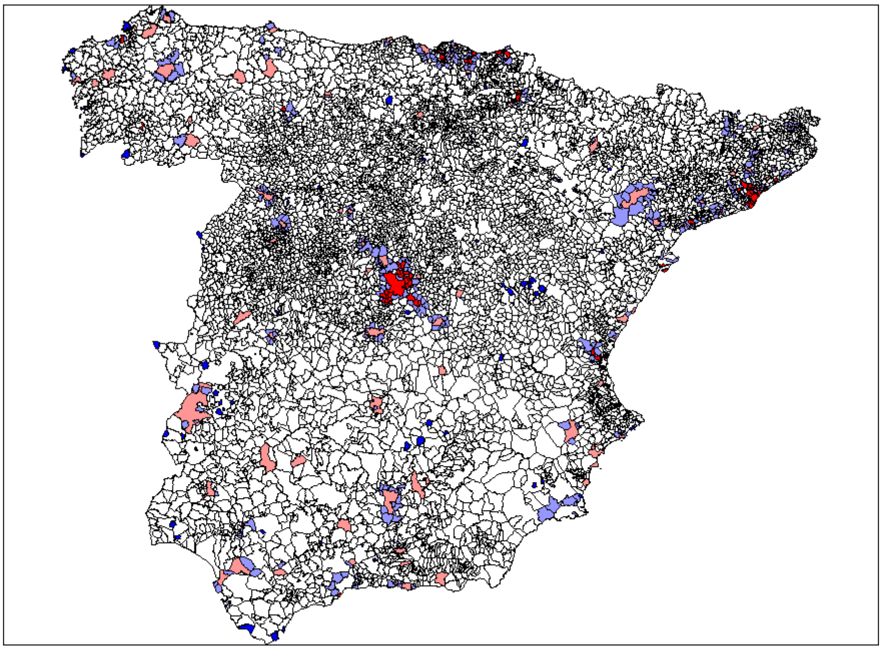


Figure 8b: 1991-1995



upper outliers no new establishments

Figure 9: Local Moran's I map for specialisation in computer and office equipment manufacturing industry



Spatial association				
Not significant		☐		
Positive	high-high	■	low-low	■
Negative	low-high	■	low-high	■

Table 4: Spatial autocorrelation statistics: computers and office equipment

Table 4.1 Moran's I test

a) Normal approach

Variable	I	Mean	St.Dev.	Z-Value	Prob
LQ	0.04510711	-0.000	0.006559	6.895961	0.000000

b) Empirical pseudo-significance based on 99 random permutations

Variable	I	Mean	St.Dev.	Prob
LQ	0.04510711	0.001	0.008131	0.020000

c) Randomization assumption)

Variable	I	Mean	St.Dev.	Z-Value	Prob
LQ	0.04510711	-0.000	0.006559	6.895961	0.000000

Table 4.2 BB Joint Count test

Variable	BB	Mean	St.Dev.	Z-Value	Prob
LOC_{86}	15	1.159241	1.076160	12.861243	0.000000
LOC_{87}	34	2.499897	1.580235	19.933813	0.000000
LOC_{88}	30	3.220282	1.793468	14.931804	0.000000
LOC_{89}	14	0.849107	0.921042	14.278283	0.000000
LOC_{90}	17	0.849107	0.921042	17.535465	0.000000
LOC_{91}	21	0.998152	0.998602	20.029848	0.000000
LOC_{92}	15	1.159241	1.076160	12.861243	0.000000
LOC_{93}	22	1.287962	1.134327	18.259312	0.000000
LOC_{94}	18	0.998152	0.998602	17.025649	0.000000
LOC_{95}	16	0.922124	0.959822	15.709032	0.000000

LQ = Location quotient; LOC = Creation of manufacturing establishments

TABLE 5 ALIMENTOS, BEBIDAS Y TABACOFOOD, DRINKS AND TOBACCO														
	PoissonPoisson				Binomial negativaNegative Binomial				Spatial Error Model			Spatial Autoreg. Model		
	Coef	St.Er.	Z	P>|z|	Coef	St.Er.	z	P>|z|	Coef	St.D.	Prob.	Coef	St.D.	Prob.
Const	-3,11928	0,090	-34,48	0,000	-4,20349	0,176	-23,88	0,000	-2,45233	0,078	0,000	-2,11714	0,095	0,000
ACC	-0,00012	0,000	-10,88	0,000	-0,00003	0,000	-1,63	0,103	-0,00004	0,000	0,000	-0,00001	0,000	0,188
HC	5,49610	0,144	38,25	0,000	5,22839	0,412	12,68	0,000	1,84283	0,208	0,000	1,25482	0,245	0,000
LVA	0,00062	0,000	50,31	0,000	0,00891	0,001	9,53	0,000	0,00435	0,001	0,000	0,00743	0,002	0,000
DI	0,97795	0,019	52,06	0,000	1,58610	0,086	18,52	0,000	1,53336	0,058	0,000	1,50986	0,072	0,000
LQ	0,00293	0,001	4,69	0,000	0,02556	0,006	3,97	0,000	0,00302	0,001	0,015	0,00256	0,002	0,097
IAF														
λWe									0,32620	0,023	0,000			
ρWLOC												0,32959	0,021	0,000
WHC	-4,38319	0,282	-15,54	0,000	-4,91820	0,572	-8,6	0,000						
WLVA	0,00315	0,000	12,74	0,000	0,00377	0,001	3,1	0,002						
WDI	2,15574	0,069	31,15	0,000	2,55770	0,147	17,36	0,000						
WLQ	0,00248	0,001	2,79	0,005	-0,00064	0,004	-0,17	0,865						

TABLE 6 QUÍMICACHEMISTRY														
	PoissonPoisson				Binomial negativaNegative binomial				Spatial Error Model			Spatial Autoreg. Model		
	Coef	St.Er.	z	P>|z|	Coef	St.Er.	z	P>|z|	Coef	St.D.	Prob.	Coef	St.D.	Prob.
Const	-5,37410	0,175	-30,79	0,000	-6,89745	0,312	-22,13	0,000	-3,08225	0,111	0,000	-2,68885	0,125	0,000
ACC	-0,00026	0,000	-9,82	0,000	-0,00018	0,000	-5,23	0,000	-0,00012	0,000	0,000	-0,00007	0,000	0,000
HC	3,58751	0,263	13,66	0,000	5,39448	0,632	8,54	0,000	2,41789	0,259	0,000	1,89742	0,294	0,000
LVA	0,00025	0,000	9,27	0,000	0,00442	0,001	5,2	0,000	0,00471	0,001	0,000	0,00762	0,002	0,000
DI	1,16495	0,031	38,19	0,000	1,66082	0,113	14,64	0,000	1,42814	0,070	0,000	1,11276	0,081	0,000
LQ	0,08972	0,004	25,45	0,000	0,21904	0,025	8,72	0,000	0,14273	0,016	0,000	0,14934	0,021	0,000
IAF														
λWe									0,07164	0,028	0,002			
ρWLOC												0,13275	0,025	0,000
WHC	0,68771	0,501	1,37	0,170	-0,60269	0,957	-0,63	0,529						
WLVA	-0,00129	0,000	-2,67	0,007	-0,00106	0,001	-0,72	0,472						
WDI	2,21034	0,129	17,16	0,000	2,78357	0,234	11,91	0,000						
WLQ	0,29776	0,038	7,84	0,000	0,26328	0,094	2,79	0,005						

TABLE 7 COMPUTERS AND OFFICE EQUIPMENT															
	Poisson				Negative binomial				Spatial Error Model			Spatial Autoreg. Model		
	Coef	St.Er.	Z	P>|z|	Coef	St.Er.	z	P>|z|	Coef	St.D.	Prob.	Coef	St.D.	Prob.
Const	-6,89775	0,421	-16,38	0,000	-8,23490	0,683	-12,06	0,000	-3,23440	0,172	0,000	-2,59832	0,144	0,000
ACC	-0,00044	0,000	-5,45	0,000	-0,00033	0,000	-3,6	0,000	-0,00009	0,000	0,000	-0,00003	0,000	0,069
HC	7,48773	0,505	14,84	0,000	7,94248	1,167	6,8	0,000	2,47817	0,393	0,000	1,10026	0,366	0,002
LVA	0,00064	0,000	17,05	0,000	0,00678	0,001	5,07	0,000	0,00506	0,001	0,000	0,00903	0,001	0,000
DI	1,14929	0,062	18,62	0,000	1,16839	0,213	5,49	0,000	0,62637	0,092	0,000	0,23968	0,089	0,001
LQ	0,04871	0,009	5,51	0,000	0,06981	0,024	2,89	0,004	0,03617	0,009	0,000	0,03268	0,012	0,002
IAF														
λWe									0,01373	0,029	0,346			
ρWLOC												0,03020	0,027	0,132
WHC	-3,76187	1,157	-3,25	0,001	-3,16493	1,899	-1,67	0,096						
WLVA	0,00126	0,001	1,47	0,141	0,00190	0,002	0,94	0,349						
WDI	1,95396	0,292	6,7	0,000	2,45206	0,470	5,22	0,000						
WLQ	0,27670	0,046	5,98	0,000	0,26350	0,098	2,7	0,007						

7. References

Alañón, Angel 2004. “Un modelo espacial de renta per cápita regional: evidencia provincial, comarcal y municipal,” *Investigaciones Regionales*, 4, 99-114.

Alañón, Angel 2002. “Estimación del valor añadido per cápita de los municipios españoles en 1991 mediante técnicas de econometría espacial,” *Ekonomiaz,* 51, 172-194.

Alañón, Angel and Myro, Rafael 2005. “Does neighboring industrial atmosphere matter in industrial location? Empirical evidence from Spanish municipalities,” *Estudios de Economía Española* 199, FEDEA.

Anselin, Luc 2005. “Exploring Spatial Data with GeoDaTM : A Workbook, Spatial Analysis Laboratory,” Department of Geography, University of Illinois, Urbana-Champaign, Urbana, IL 61801, Center for Spatially Integrated Social Science.

Anselin, Luc 2003. “GeoDa™ 0.9 User’s Guide”, Spatial Analysis Laboratory, Department of Agricultural and Consumer Economics, University of Illinois, Urbana-Champaign, Urbana, IL 61801.

Anselin, Luc 2002. “Under the Hood. Issues in the Specification and Interpretation of Spatial Regression Models”, *Agricultural Economics*, 17, 247-267.

Anselin, Luc 1992. SpaceStat Tutorial. “A woorbook four using SpaceStat in the analysis of spatial data”, University of Illinois, Urbana Champaign, Urbana, IL 61801.

Anselin, Luc 1988. *Spatial Econometrics: Methods and models.* Dordrecht: Kluewer Academic Publishers.

Arauzo, Josep Maria 2008. “Industrial Location at a Local Level: Comments on the Territorial Level of the Analysis”, *Tijdschrift voor Economische en Sociale Geografie-Journal of Economic & Social Geography*, 99 (2), 193-208.

Arauzo, Josep Maria 2005. “Determinants of Industrial Location. An Application for Catalan Municipalities”, *Papers in Regional Science,* 84, 105-120.

Arbia, Giuseppe 2005. Introductory spatial econometrics with applications to regional convergence. Berlin: Springer-Verlag.

Arbia, Giuseppe 1989. Spatial data configuration in statistical analysis of regional economic and related problems. Dordrecht: Kluwer Academic Publishers.

Aschauer, David Alan 1989. “Is Public expenditure productive?,” *Journal of Monetary Economics,* 23, 177-200.

Audretsch, David B. and Feldman, Maryann P. 1996. “R&D spillovers and the geography of innovation and production,” *American Economic Review,* 86, pp. 630-640.

Beckman, Matthew J. 2000. “Interurban Knowledge Networks, in D. Batten et al. (Eds.) *Learning,” Innovation and the Urban Evolution*, 127-135. London: Kluwer Academic Publishers.

Boarnet, Marlon G. 1998. “Spillovers and the locational effects of public infrastructure,” *Journal of Regional Science,* 38, 381-400.

Cameron, A. Colin and Trivedi, Pravin K. 1998. *Regression analysis of count data*, Cambridge University Press.

Carlino, Gerald A. and Mills, Edwin S. 1987. “The determinants of county growth,” *Journal of Regional Science,* 27, 39-54.

Carlino, Gerald A. and Voith, Richard 1992. “Accounting for differences in aggregate state productivity,” *Regional Science and Urban Economics,* 22, 597-617.

Chandra, Amitabh and Thompson, Eric 2000. “Does public infrastructure affect economic activity? Evidence from the rural interstate highway system,” *Regional Science and Urban Economics,* 30, 457-490.

Ciccone, Antonio and Hall, Robert 1996. “Productivity and the density of economic activity,” *American Economic Review*, 86, 54-70.

Cieślik, Andrzej 2005. “Regional characteristics and the location of foreign firms within Poland,” *Applied Economics* 37, 863-874.

Cliff, Andrew and Ord, Keith 1980. *Spatial processes models and applications*, London: Pion.

Coughlin, Cletus C. and Segev, Eran 2000. “Location determinants of new foreign-owned manufacturing plants”, *Journal of Regional Science* 40, 323-351.

Duranton, Gilles and Puga, Diego 2000. “Diversity and specialisation in cities, why, where and when does it matters?,“ *Urban Studies,* 37, 533-555.

Ellison, Glenn and Glaeser, Edward 1997. “Geographic Concentration in US Manufacturing Industries, A Dartboard Approach,” *Journal of Political Economy,* 105, 889-927.

Figueiredo, Octávio, Guimarães, Paulo, and Woodward, Douglas 2002. “Home-field advantage location decisions of Portuguese entrepreneurs,” *Journal of Urban Economics,* 52, 341-361.

Fleming, Mark 2004. *Techniques for estimating spatially dependent discrete choice models in: L. Anselin, R. J. G. M. Florax and S. J. Rey (Eds.) Advances in Spatial Econometrics, Methodology, Tools and Applications*, pp. 145-167. Berlin: Springer.

Friedman, Joseph; Gerlowski, Daniel A. and Silberman, Johnathan 1992. “What attracts foreign multinational corporations? Evidence from branch plant location in the United States”, *Journal of Regional Science* 32, 403-418.

Fujita, Masahisa, Krugman, Paul and Venables, Anthony J. 1999. *The Spatial Economy. Cities, Regions and International Trade*, Cambridge: The MIT Press.

García-Milà, Teresa and García-Montalvo, José 2007. “The impact of new highways on business location: new evidence from Spain”, CREI Working Papers.

García-Milà, Teresa and McGuire, Therese J. 1992. “The contribution of publicly provided inputs to states’ economies,” *Regional Science and Urban Economics,* 22, 229-241.

Glaeser, Edward; Kallal, Hedi; Scheinkman, José and Shleifer, Andrei 1992. “Growth in cities,” *Journal of Political Economy,* 100, 1126-1152.

Guimarães, Paulo, Figueiredo, Octávio and Woodward, Douglas 2004. “Industrial location modeling extending the random utility framework,” *Journal of Regional Science,* 44, 1-20.

Guimarães, Paulo, Figueiredo, Octávio and Woodward, Douglas 2000. “Agglomeration and the Location of Foreign Direct Investment in Portugal,” *Journal of Urban Economics,* 47, 115-135.

Haughwout, Andrew F. 1999. “State Infrastructure and the Geography of Employment,” *Growth and Change,* 30, 549-566.

Hayter, Roger 1997. *The dynamics of industrial location. The factory, the firm and the production system*, Wiley.

Henderson, Vernon, Kuncoro, Ari and Turner, Matt 1995. “Industrial development in cities,” *Journal of Political Economy*, 103 (5), 1067-1090.

Holl, Adelheid 2004A. “Manufacturing location and impacts of road transport infrastructure Empirical evidence from Spain,” *Regional Science and Urban Economics,* 34, 341-363.

Holl, Adelheid 2004B. “Transport infrastructure, agglomeration economies, and firm birth Empirical evidence from Portugal,” *Journal of Regional Science,* 44, 693-712.

Holl, Adelheid 2007. “Twenty years of accessibility improvements. The case of the Spanish motorway building programme,” *Journal of Transport Geography***,** 15, 286-297

Jacobs, Jane 1969. *The Economy of Cities*, New York: Vintage Books.

Kaiser, Mark and Cressie, Noel 1997. “Modeling Poisson variables with positive spatial dependence,” *Statistics & Probability letters,* 35, 423-432.

Krugman, Paul 1993. “First nature, second nature, and metropolitan location,” *Journal of Regional Science*, 33, 129-144.

Lesage, James 2000. “Bayesian estimation of limited dependent variable spatial autoregressive models,” *Geographical Analysis,* 32, 19–35.

Lesage, James 1997. “Bayesian Estimation of Spatial Autoregressive Models,” *International Regional Science Review,* 20, 113-129.

List, John A. 2001. “US county-level determinants of inbound FDI: evidence from a two-step modified count data model”, *International Journal of Industrial Organization* 19, 953-973.

Mas, Matilde, Maudos, Joaquín, Pérez, Francisco and Uriel, Ezequiel 1996. “Infrastructure and Productivity in the Spanish Regions,” *Regional Studies,* 30, 641-649.

McCann, Philip. 2001 *Urban and Regional Economics*, Oxford, Oxford University Press.

Mcmillen, Daniel 1995. “Spatial effects in Probit models: a Monte Carlo investigation, in: L. Anselin and R. Florax (Eds.)” *New Directions in Spatial Econometrics*, 189–228. Berlin: Springer.

Mompó Angel and Monfort Vicente 1989. “El Registro Industrial como fuente estadística regional: el caso de la Comunidad Valenciana.” *Economía Industrial* 268, 129-140

OECD 2001. “Main Science and Technology Indicators 2000.” OECD, Paris.

Papke, Leslie 1991. “Interstate business tax differentials and new firm location”, *Journal of Public Economics* 45, 47–68.

Pablo-Martí, Federico and Myro, Rafael 2006. “Impacto potencial del PET sobre la accesibilidad del territorio español por carretera” *Economistas* 110, 81-88.

Pinkse, Joris and Slade, Margaret 1988. “Contracting in Space: An Application of Spatial Statistics to Discrete-Choice Models,” *Journal of Econometrics,* 85, 125-154.

Richardson, Harry 1978. *Regional and urban economics.* Harmondsworth: Penguin.

Rosenthal, Stuart S. and Strange, William C. 2003. “Geography, industrial organization and agglomeration,” *The Review of Economics and Statistics,* 85, 377-393.

Smith, Tony and Lesage, James P. 2002. “A Bayesian Probit Model with Spatial Dependencies,” available in www.spatial-econometrics.com.

Viladecans, Elisabet 2004. “Agglomeration economies and industrial location city-level evidence,” *Journal of Economic Geography,* 4, 565-582.

Weber, Alfred 1929. *Theory of the Location of Industries.* Chicago: Chicago University Press, ed. of 1965.

Woodward, Douglas 1992. “Locational determinants of Japanese manufacturing start-ups in the United States”, *Southern Economic Journal* 58, 690–708.

[1] 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 (in minutes) 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.

[2] See Holl (2007) for a summary of the effects of the Spanish motorway building programme.

[3] Alfred Marshall (1920) analysed advantages linked to the geographical concentration of economic activity (agglomeration economies) and summarised them into three main advantages: specialised labour markets, availability of suppliers and knowledge spillovers.

[4] Specifically, better infrastructure networks mean lower transportation costs, which could attract new firms to those sites.

[5] Also from a territorial point of view, Mas et al. (1996) show the positive effects of infrastructures on the Spanish economy.

[6] We have used data from almost all Spanish municipalities (specifically, 7915 municipalities). Due to the non spatial contiguity of municipalities located on islands, and outside the European continent we have left

out data from the Balearic Islands, the Canary Islands, and Ceuta and Melilla (two cities located in northern Africa). Finally, we decided to leave out certain municipalities with no reliable data.

[7] See Mompó and Montfort (1989) for a description of the dataset.

[8] The REI dataset collects information about the location of manufacturing establishments, regardless of whether they are new or relocated firms.

[9] 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).

[10] However, if an industry is not present in most municipalities, then the circle would be red, even if a municipality is not particularly specialised in that industry, because in most municipalities the value of the location quotient would be zero.

[11] 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.

[12] Before introducing our model we must 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.

[13] Local tax data are not available due to statistical secrecy. If we used provincial NUTs III data to act as a proxy for local data on taxes, labour costs or land prices, we would fall into an ecological fallacy and Modifiable Areal Unit problems (see Anselin (1988) or Arbia (1989) 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).

[14] See Pablo-Martí and Myro (2006) for a detailed analysis of this indicator.

[15] 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.

[16] See Arauzo (2008) for a review of the methodological issues regarding industrial location literature.

[17] See Cameron and Trivedi (1998) for a detailed analysis of the “zero problem”.

[18] 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. See Kaiser and Cressie (1997) or Arbia (2005) for a more detailed discussion.

[19] $\varepsilon \approx N(0,\sigma^2 V), V = diag(v_1, v_2, ..., v_n)$.

[20] The estimated coefficients are not standardized. Both accessibility –ACC- and internal market –LVA- coefficients are very low because of the units used to build the indicators. SAR and SEM coefficients are restricted to the [-1,1] range. Information about goodness of fit indicators it is not shown because these indicators cannot be used to compare Poisson, Negative Binomial, SAR and SEM models.

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