Industrial location, spatial discrete choice models and the need to account for neighbourhood effects

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Abstract. This research, following the pioneering contributions of Autant-Bernard (European Planning Studies 14:1187-1208, 2006) and Vichiensan et al. (Journal of the Eastern Asia Society for Transport Studies 6:3789-3802, 2005), extends the spatial conditional logit model in order to account for the role that neighbourhood effects play in the firms' location choices, defining a theoretical model where externalities or spillover effects now enter the decision-maker's information set. We apply this new methodology to a sample of 8,000 industrial establishments at the municipality level, with our results showing that supply-side location factors, such as human capital and agglomeration economies, together with institutional factors, i.e. industrial land availability, are the main forces driving entrepreneurs' decisions. Furthermore, results on the spatial component of the model show that inter-municipal spillovers have a remarkable influence on the location decisions of the firms. Particularly, we observe that attributes of neighbouring municipalities are found to exert nearly the same influence as those of the chosen municipality in guiding one firm's choice, thus confirming the need to account for such spatial interdependences when studying location choices of industrial companies at a local level.

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1 Introduction

When deciding to start a new business, the choice of where to locate the facilities is one of the most crucial steps of the process. This decision is so important that it could determine the success not only of the firm's current activity but also its future (Strotmann 2007). Increasing complexity is undoubtedly a feature of today's international economy with many variables affecting location decisions, making this a key issue in the firms' strategies. In this context, it is not difficult to understand why we have seen a renewal of interest in location studies in recent decades (McFadden 2001; McCann and Sepphard 2003).

Empirical studies of industrial location have been one of the most active lines of research in this field since the late 1980s, with academic contributions trying to identify the main factors driving firms' choices. From a methodological point of view, the study of the determinants of industrial location follows two different econometric approaches, namely Discrete Choice Models (DCMs) and Count Data Models (CDMs) (Arauzo et al. 2006). On one hand, DCMs analyse the way in which the characteristics of the decision-maker, such as firm size, sector of activity, etc., affect the choice itself, constrained to the set of geographical alternatives available (Mc Fadden 1974; Carlton 1983). On the other hand, CDMs confront the decision problem by investigating which of the characteristics of an area affect the number of companies established in that particular location for a certain period of time (Becker and Henderson 2000).

In terms of computational requirements, both approaches have their own pros and cons, with DCMs allowing for a richer information set combining both firm/plant and spatial unit characteristics, while CDMs appear more tractable in order to compute the likelihood function if the number of alternatives becomes too large. However, both approaches rely on the same theoretical framework, a profit maximisation problem in which the firm chooses the location that reports the higher expected profit, given standard constraints (Mc Fadden 2001; Mc Fadden 1978; Carlton 1983). As some authors have noted, we can even think of both models as reduced-form results coming from the same location choice structural model. For this reason, this methodological framework has proved extremely useful, given the flexibility and degree of generality that it allows, becoming a standard in the literature (Guimarães et al. 2004; Becker and Henderson 2000).

It is worth noting that in this theoretical framework the decision-maker simply uses information on every individual location when computing the expected profit from locating in that particular spatial unit. However, as the spatial economy literature highlights, the value achieved by a variable (i.e. profits) in one particular location may be affected by the realisation of the same, or other, variables in nearby locations because of spatial dependence effects (Anselin 1988) and the presence of external economies and spillovers (Ellison and Glaeser 1997; Fujita and Thisse 2002). On this point, it seems reasonable that a more appropriate location choice model should incorporate these potential spatial effects into the decision-making process.

Despite the importance that the topic of location choices has shown in guiding the decisions of entrepreneurs, managers and policy makers, and although this has proved to be a very fertile field of research, little work has been done to date on incorporating spatial dependence in location choice models, particularly for the discrete choice framework (Fleming, 2004). Early contributions in this literature take the simple form of spatial binary choice models (Murdoch et al. 2003; Marsh et al. 2000), with recent developments of spatial probit models (Coughlin et al. 2004; Holloway et al. 2002) since the launch of the Spatial Econometrics toolbox for MATLAB by professor James P. Le Sage. Other recent contributions include the use of spatial multinomial logit models, with interesting applications to environmental and transport planning studies (Nelson et al. 2004; Mohammadian et al. 2003), but the literature is clearly at a very early stage concerning the use of spatial conditional logit models, the family of DCMs usually employed in industrial location studies.

To the best of our knowledge, only two references appear in the literature. The first one is the paper by Vichiensan, Miyamoto and Tokunaga (2005), which extends the conditional logit model by considering a spatial autoregressive structure in both the deterministic and the stochastic part of the model specification. The idea is to capture external economies that influence the decision-maker in his/her location choice. However, the exercise is devoted to a residential choice analysis in Senday City (Japan), and its focus is more on identifying how the geographical dispersion of alternatives affects the decision-maker's choice. In their exercise, the significance of the spatial variable of the model appears to be highly dependent on the spatial pattern that characterises location alternatives. The main drawbacks of this approach stem from the computational difficulties it poses with a large set of alternatives, as estimation would turn into a very complex, maybe unfeasible, task.

The second reference is that of Autant-Bernard (2006), who implements a conditional logit model in order to search for the location determinants of R&D laboratories in France. The unit of analysis is the administrative region (NUTS 2) and the model incorporates a spatially lagged term for every explanatory variable in order to determine the spatial scope of knowledge spillovers. The estimation results show that only private R&D expenditure appears to generate inter-regional knowledge spillovers that influence location decisions of R&D labs in France.

In this context, the aim of our paper is to continue extending the spatial conditional logit framework for industrial location studies. Two contributions are made to the literature. The first one is analytical, consisting in using municipalities as the geographical unit of analysis, which allows us to better account for the existence of spatial spillovers from a firm's perspective, as recent contributions have noted (Arauzo 2008; Holl 2004). The second one, which constitutes the real core of the paper, is methodological, and seeks to specify a theoretical model where externalities or spillover effects enter the decision-maker's information set. But, in line with the spatial econometrics approach and departing from previous contributions, we propose to approach these neighbourhood effects using a synthetic measure combining both social and economic characteristics linked to nearby areas, specifying in this way a unique source of spillovers that captures all of the spatial effects affecting the firm's choice; an approach we think is closer to the theoretical concept of spatial dependence.

To this purpose, we develop a new framework that accounts for spatial effects in the firms' decision process. After that, we apply our new methodology, studying the factors driving location choices of more than 8000 industrial establishments in the Spanish NUTS 2 Region of Murcia. Availability of detailed micro-data containing the main characteristics of industrial firms and territorial units (municipalities) for this region offers an excellent opportunity for obtaining empirical evidence on the performance of our new methodological proposal. To anticipate some of the results, we find that human capital, agglomeration economies and industrial land availability are the main forces driving location decisions for industries in this region, with results on the spatial component of the model showing that external economies or spillovers have a remarkable influence on firms' location decisions. Attributes of neighbouring municipalities are found to exert nearly the same influence as those of the chosen municipality in guiding the decision-maker's choice, thus confirming the need to account for such spatial interdependences when studying location choices of industrial companies at a local level.

After this introduction, the rest of the paper is organised as follows. In section 2 we develop our theoretical model. Section 3 includes the discussion of the database, presents the econometric model and includes the empirical results of the paper, while section 4 reports the conclusions of the research.

2 Spatial discrete choice models and location processes

Our theoretical model builds on the standard random utility maximisation (RUM) framework employed to analyze the firms' location behaviour. In this framework, firm i decides where to locate, among a finite set of J location alternatives (municipalities), according to the expected profit that every location j is reporting. The choice could be described as a maximisation problem of the profit function of the firm, a function given by:

$$\pi_{ij} = X_j \beta + \varepsilon_{ij}, \qquad i = 1,..., N;\ j = 1,..., J\ . \tag{1}$$

where X_j is a $1 \times M$ vector of local geographic and economic conditions, β is a vector of parameters, and ε_{ij} is a random error term capturing the characteristics of the decision-maker or unobservable attributes of the choices.[1] Under profit-maximising behaviour, location in municipality *j* is chosen by the firm *i* whenever,

$$\pi_{ij} \geq \pi_{ik}, \quad \forall k \neq j,\ k = 1, ..., J \ . \tag{2}$$

that is, the alternative *j* is chosen when its attributes ensure the greatest expected profits to the firm. Therefore, the probability that a firm *i* is located in the municipality *j*, given its characteristics and those of the alternative locations, yields

$$P_j = \Pr\left(\pi_{ij} \geq \pi_{ik}, \forall k \neq j, k = 1, ..., J\right). \tag{3}$$

It can be shown that, if disturbances are independent and identically distributed following a Weibull distribution, then the probability that the firm *i* chooses alternative *j* is (Greene 2008),

$$P_j = \frac{\exp\left(X_j \beta\right)}{\sum_{k=1}^{J} \exp\left(X_k \beta\right)}. \tag{4}$$

At this point, it should be noted that in the standard (conditional logit) framework the firm uses information on both the characteristics of the chosen location (*j*) and those of the alternatives (*k* =1,…,*J*) when taking its choice (see equation (4)). However, when computing the profits function of locating in municipality *j*, the decision-maker is using only information on that individual location, losing all other information sourced by neighbouring locations (see equation (1)). By contrast, empirical evidence and the same literature on industrial location determinants suggest that expected profits from locating in a particular municipality are also influenced by economic and social activity taking place in the neighbouring areas, given the potential existence of externalities or spillovers (Arauzo et al 2006; Fujita and Thisse 2002; Arbia 2001), the same effects hitherto neglected by the standard theoretical model of (industrial) location choice.

[1] The error term is assumed to be uncorrelated across choices, what leads to the usual assumption on the independence of irrelevant alternatives (Carlton 1983; McFadden 1974).

In this context, our approach pursues introducing this stylised fact in the theoretical framework by accounting for the influence of these *"neighbour area attributes"* on the firm's profit function and consequently on its location choice, entering the model as an important component of the decision-maker's information set.[2] In order to introduce this "neighbourhood" component in location models, we propose to modify the systematic part of equation (1) by including a term that captures the potential spillovers influencing the decision of the firm as follows:[3]

$$\pi_{ij} = X_j\beta + \delta\sum_{l=1}^{J} w_{jl} X_l \beta + \varepsilon_{ij}, \quad i = 1,..., N;\ j = 1,..., J\ , \tag{5}$$

where $\{w_{jl}\}_{l=1,...,J}$ is a weighting sequence defined in terms of the distance between municipalities *j* and *l*. In general, we still do not address any precise definition of distance, which could be based on economic, geographic, or socio-cultural considerations.[4]

The proposed extension of the model shows, as seen in equation (5), that now the expected profits of locating in municipality *j* would depend not only on the attributes collected by X_j, but additionally on the *spatially weighted average* of the attributes of alternative locations. Consequently, the parameter δ would be, by definition, a synthetic measure of the strength that neighbourhood effects detent when affecting the choice of firm *i*, by influencing its expected profits' function. This approach clearly departs from previous contributions in the literature, improving them in two ways: first theoretically, allowing for the inclusion of these neighbourhood effects as an extension of the model (McFadden 2001; McFadden 1978; Carlton 1983), and second empirically, providing an estimate of a single quantitative value which summarises the influence that this local dependence pattern has on the firm's choice. It is worth noting that a similar

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[2] It is important to note that although dozens of social and economic characteristics of nearby locations could influence the firm's behaviour, we are interested in including in our extended model only those that have a direct impact on the firm's expected profits, because only these would matter when constructing the firm's choice probability function (Train 2003).
[3] Note that this specification for the expected profits resembles the spatial cross-regressive model (Anselin 2003; Florax and Folmer 1992).
[4] Note that this offers the theoretical model an opportunity of becoming a valid framework for different types of location studies, as, i.e., those devoted to industrial location, marketing or even industrial organisation studies.

measurement which allows for retrieving the spatial dimension in location models is not present in this literature (Autant-Bernard 2006; Vichiensan et al. 2005). Empirically, a positive value of the spatial parameter, $\delta > 0$, would be implying that external economies play a significant role in the firm's choice, while a negative value of the parameter, $\delta < 0$, would be reflecting the existence of congestion/dispersion externalities in the chosen municipality which affect the firm's profits (Viladecans 2004).

Furthermore, if we assume that the error terms in equation (5) are independent and identically distributed following a Weibull distribution, the probability of firm i to choose municipality j is now:

$$P_j = \frac{\exp\left(X_j \beta + \delta \sum_{l=1}^{J} w_{jl} X_l \beta \right)}{\sum_{k=1}^{J} \exp\left(X_k \beta + \delta \sum_{l=1}^{J} w_{kl} X_l \beta \right)}, \tag{6}$$

from which it is straightforward to compute marginal effects as:

$$\frac{\partial P_j}{\partial X_l} = \begin{cases} P_j \left(1 - P_j\right) \beta & \text{if } l = j \\ P_j \left[\delta w_{jl} \left(1 - P_j\right) - P_l \right] \beta & \text{if } l \neq j \end{cases} \tag{7}$$

We can also define marginal effects with respect to the spatially weighted attributes, denoted by $WX_j = \sum_{l=1}^{J} w_{jl} X_l$,[5] as:

$$\frac{\partial P_j}{\partial WX_j} = \delta P_j \left(1 - P_j\right) \beta . \tag{8}$$

By comparing expressions (7) and (8) for $l = j$ we can conclude that, for the *m*-th attribute,

$$\delta = \frac{\partial P_j / \partial WX_{j,m}}{\partial P_j / \partial X_{j,m}}, \; m = 1, \ldots, M , \tag{9}$$

which means that the parameter δ is by construction measuring the *relative importance* that neighbourhood attributes have as compared to specific local attributes (of the chosen *j*-th alternative) in the decision-making problem. A value of δ greater than one would now imply that the neighbourhood attributes

[5] Note that under this notation we can rewrite the expected profit of a firm i of establishing itself in municipality j as $\pi_{ij} = X_j \beta + \delta WX_j \beta + \varepsilon_{ij}$, $i = 1, ..., N$; $j = 1, ..., J$.

affecting the decision of a firm located in the municipality *j* appear to be of greater importance than those of municipality *j* itself*;* that is, the firm locating in municipality *j* is intending to benefit more from neighbourhood advantages than from its own local advantages. By contrast, a positive value of δ below one implies that, even though spatial effects are important for the firm, they seem less important as location attractors than the specific attributes of the chosen location, what appears to be a more plausible result.[6]

3 Empirical results

3.1 Data

Having defined our new theoretical model, we are now interested in identifying the factors that are influencing the firms' location choices, and capturing the role that external economies are playing in this process through spatial spillovers. Our dependent variable is the number of industrial establishments operating at the municipality level in the Spanish Region of Murcia in 2006. This information is obtained from the Business Directory (DAERM) of the Regional Statistical Office of Murcia, which reports information on 8429 industrial establishments classified by municipality of location and sector of activity.

Using the municipality as the geographical unit of analysis is a novelty in spatial logit models, and also seems the appropriate approach in order to capture *spatial local spillovers* that influence decision-makers in their location choices. By applying this geographical focus we look to overcome a common error in spatial analysis, the so-called error measurement problem, which appears when the spatial dimension of the variable we want to measure does not properly match that of the chosen spatial unit of analysis in the research (Haining 1995; Rosenthal and Strange 2003). Moreover, as some authors have noted, this approach usually reports the most robust results on location analysis when employing

[6] Note, however, that this extended framework would open interesting research possibilities to studies analyzing the effects of congestion or negative spatial externalities on location choices, a type of study which is still rare in this literature (see, i.e., Arauzo 2006, footnote 14).

characteristics of areas as explanatory factors of location choices, as we do (Arauzo and Manjón 2004; Arauzo 2008).

The dataset also comprises information on the geographic and economic treats characterising the 45 municipalities making up the Spanish Region of Murcia, obtained from the Regional Statistical Office of Murcia, which allows us to conform the explanatory variables set of the model. Detailed information on social and economic characteristics of small territorial units is not usually available with such a degree of detail, so the existence of a richer dataset in this respect for the Region of Murcia has guided our decision to apply the new theoretical framework to the analysis of industrial location choices in this region.

We begin by introducing agglomeration variables in the explanatory set, given their central role in the literature on industrial location. In general, agglomeration effects can be defined as external effects including all economies that are an increasing function of the number of nearby firms (Head and Swenson 1995). If the firms belong to the same industry, we define these economies as localisation economies, but in case they belong to different industries they are termed diversity economies.[7]

The concept of localisation economies is intended to capture all firm's advantages generated by the concentration of industries from the same sector near one another, due to the existence of information spillovers derived from informal contacts between the staff of the firms or whatever other externalities arising because of the firms' proximity (Arauzo et al. 2006; Figueiredo et al. 2002; Head and Swenson 1995). This type of agglomeration economy is generally identified in the recent literature as Marshall-Arrow-Romer (MAR) externalities (Glaeser et al. 1992). To measure localisation economies we use a standard index capturing the degree of industrial specialisation of municipality *j*, in terms of employment,

[7] A general characterisation of agglomeration economies is due to Hoover (1936), whom defined localisation economies as those arising because of the concentration of firms from the same sector of activity, while terming as urbanisation economies to those deriving from a concentration of economic activity, whatever their source. In order to differentiate from localisation economies, we have preferred to use the concept of diversity economies furtherly developed by Jacobs, given the importance shown by this type of externality in today's post-industrial economies (see, e.g., Jacobs 1969).

in comparison with the specialisation that characterises the whole regional area (LOC).[8]

On the other hand, the existence of a considerable number of different industrial activities in the same location generates diversity economies, also named Jacobs' external economies (Jacobs 1969; Duranton and Puga 2000). The concept captures the external economies improving the firm's performance that stem from the diversity of industries (or services) surrounding the firm. Externalities arise because of enhanced local competition or due to the added-value it provides to the activities of the firm by improving access to new industrial inputs or services. In this paper, industrial diversity economies are captured by an index (DIV) computed as one minus the Herfindalh-Hirschman concentration index. Higher values of this index are associated with a more diversified local industrial environment.

Secondly, together with the agglomeration forces, as the literature on industrial location studies conveys, we must also include some supply-side location factors in our explanatory variables set. This kind of location factor is captured here by a human capital variable (HC), computed as the percentage of the labour force that has completed secondary and tertiary level education in every municipality (Coughlin et al. 1991; Coughlin et al. 2000). The importance of human capital, proxied by levels of education among the local workforce, for firms' location choices is well documented in the empirical literature. Some contributions even note the important role played by this variable in attracting industries with high knowledge content (Audrestch and Lemman 2005).

Thirdly, other municipal characteristics are included as explanatory variables, such as the total local population (TPOP) which acts as a demand-side variable, the ratio of local industrial employment to regional industrial employment (NIND) and the corresponding measure for the service sector (NSERV), both as factors reinforcing the role of sectoral specialisation of the municipality on industrial location choices, and the availability of industrial land (INDSURF)

[8] See the Appendix for a more detailed description of the explanatory variables and statistical sources employed in the econometric study.

serving as an endowment variable reflecting local and regional efforts to provide the necessary conditions for attracting new industries (Woodward 1992; Guimarães et al. 1998). As one can see, our pool of locational factors basically includes neoclassical factors, as we are embedded in a profit maximising framework, but also includes an endowment factor in order to account for institutionally-driven factors (Arauzo et al. 2006).

All expected coefficients for the explanatory variables of the model are assumed to be positive, as all of them strengthen the relative position of a municipality as a potential location for firms, as pointed out by the literature (Arauzo et al. 2006; Viladecans 2004).

Our final specification for the expected profit of firm *i* when establishing in municipality *j* is then given by,

$$\begin{aligned}\pi_{ij} &= \beta_1 LOC_j + \beta_2 DIV_j + \beta_3 HC_j + \beta_4 TPOP_j + \beta_5 NIND_j + \beta_6 NSERV_j \\ &+ \beta_7 INDSURF_j + \delta\left(\beta_1 WLOC_j + \beta_2 WDIV_j + \beta_3 WHC_j + \beta_4 WTPOP_j\right. \\ &\left. + \beta_5 WNIND_j + \beta_6 WNSERV_j + \beta_7 WINDSURF_j\right) + \varepsilon_{ij}\end{aligned} \tag{10}$$

where the spatially weighted averaged variables are computed using a weight matrix *W*, what constitutes a standard of the spatial econometrics approach (Anselin 1988).

The weighting scheme of our neighbourhood attributes will obviously depend on the definition of distance used. Here we adopt a standard spatial econometrics approach by defining the weights in terms of the inverse Euclidean distance between municipalities. The exact definition then yields:

$$w_{jl} = \begin{cases} 0 & \text{if } j = l \\ \dfrac{d_{jl}^{-1}\mathbf{1}_{(d_{jl} \le R)}}{\sum_{l=1}^{J} d_{jl}^{-1}\mathbf{1}_{(d_{jl} \le R)}} & \text{if } j \ne l \end{cases}$$

where d_{jl} is the Euclidean distance between municipalities *j* and *l*; $\mathbf{1}_{(\cdot)}$ is an index function that equals 1 when the municipality *l* is within a circle with radius *R* and centre in the municipality *j*, and zero otherwise. It is equally important to note that this definition of distance implies that in the decision of locating in municipality *j*, the firm is just taking into account the characteristics of the nearby municipalities which lie inside the defined circle, which we term as neighbours. This approach allows us to calibrate the extent to which spillovers exert an effect on the firm's profits function, adding some rationale in line with the most recent industrial location literature on spatial spillovers (Arauzo 2005).

3.2 Some econometric issues about the estimation procedure

The parameters β and δ in equation (10) can be estimated by maximising the log-likelihood function,

$$\log L_{cl} = \sum_{i=1}^{N}\sum_{j=1}^{J} \log P_j = \sum_{j=1}^{J} n_j \log P_j \, , \tag{11}$$

where n_j is the number of firms which have chosen municipality *j*.

As we have mentioned, from a computational point of view, estimating the resulting spatial conditional logit by maximum likelihood methods may be cumbersome, especially when the number of alternatives or locations becomes large enough. Although this is not now the case, we decide to follow the estimation procedure proposed by Guimarães et al. (2003) when estimating our spatially extended model, consisting of recovering conditional logit parameter estimates from CDMs results, given that the main contribution of the paper is methodological and in this way it could easily be generalised to other empirical studies which certainly share this problem.

As these authors demonstrate, there is an equivalence relationship between the conditional logit and Poisson likelihood functions. In this way, if we assume that n_j is Poisson distributed variable, with mean

$$\mathrm{E}\left(n_j\right) = \exp\left(\alpha + X_j\beta + \delta\sum_{l=1}^{J} w_{jl} X_l \beta\right). \tag{12}$$

then the (concentrated) likelihood function for this Poisson regression model is,

$$\log L_p = -N + N\log N + \sum_{j=1}^{J} n_j \log P_j - \sum_{j=1}^{J} \log(n_j !) \, , \tag{13}$$

where the third term exactly matches the likelihood function of the spatial conditional logit model and the other three terms do not depend on the parameters vector, remaining constant for a particular dataset. It then would follow that the parameters in the spatial conditional logit model (5) can be estimated departing from those using a Poisson regression. After applying this methodological proposal, in the next subsection we discuss the estimation results of our econometric model.

3.3 Results

A first look at the distribution of industrial establishments in the Region of Murcia shows the existence of an important degree of firm clustering, with four municipalities, Murcia, Cartagena, Lorca and Yecla, accounting for more than half (56%) of the total number of establishments (DAERM database). This clustering pattern is equally reflected by the percentile map in Figure 1, which includes information on the distribution of industrial establishments over regional municipalities. One municipality, the city of Murcia, stays in the upper percentile, thus appearing to be the more attractive location for establishing an industrial company, while other four municipalities – Cartagena, Lorca, Yecla and Molina de Segura – are situated in the percentile range immediately below it, sharing a similar capacity to attract industries.[9] The other regional municipalities are not so important in the regional arena, although we must distinguish between the intermediate group, made up of 19 municipalities, and the three other percentile groups occupying the last positions in the distribution of regional industries, with 21 municipalities – nearly half of the total of 45 in the region – accounting for just 10% of total regional establishments (DAERM database). Table 1 shows us the important degree of sectoral specialisation that characterises the regional industry, in which just three sectors account for 50.5% of total industrial establishments: food industries, steel and metal products, and furniture and other manufactured goods. These industries are largely established in the city of Murcia and Cartagena, with the furniture industry mainly established in Yecla and the food industry showing an important presence in Cartagena and Lorca.

[9] The city of Murcia is the red-coloured municipality in Figure 1, with Molina de Segura located just above this municipality, Cartagena just below, Lorca on the left and Yecla right at the top of the map.

The results of estimating the conditional logit model are shown in Table 2.[10] The first and second columns summarise the estimation results obtained from applying the standard conditional logit specification; that is, without including cross spatial dependences between firms. On the other hand, the third and fourth columns include estimates of the model once a spatially weighted average of the neighbour's attributes has been incorporated as an additional explanatory variable, as described in the previous section. Table 2 also reports a collection of statistical measures of the goodness-of-fit of the model, also testing some hypotheses on the correspondent value of our spatial parameter of interest δ .

Regarding the value of the radius R used to compute the spatial weight sequence, and given that we do not have any *a priori* information on the true value of the parameter, we decide as a criterion of selection to choose the value of the parameter that maximised the likelihood function for the proposed specification of the model. After implementing this grid search procedure over a range from 25 km to the maximum distance between municipalities in the region, the preferred specification has been those one with a correspondent value for radius R of 43.6 km (see Figure 2).[11]

Turning now to the estimation results (Table 2, columns 1 and 2), it is remarkable that, except for the case of NSERV, the sign for the locational factors is consistent with the industrial location theory in all cases (Arauzo et al. 2006), and all estimated coefficients appear to be highly significant. Goodness-of-fit measures are in line with other empirical contributions in the literature, with an important level of significance for the joint model. In general, the standard (conditional logit) model results show that neoclassical factors continue to play an important role in influencing firms' choices at the local level. Agglomeration economies, both localisation and diversity ones, appear as key variables in driving this

[10] Estimation was carried out by using the GAUSS CML module.

[11] Looking more deeply for reasons affecting this issue, we must note that the average distance between the municipalities in the Region of Murcia is of 45.3km, so our modelling approach to the issue seems to work reasonably well in empirical terms. Alternatively, two studies on the Spanish economy estimate an average radius of 15-30km. for the local markets of the municipalities of Catalonian and Valencian regions (Viladecans 2001, 2004). In this respect, and given that the municipalities of the Region of Murcia are slightly larger in terms of average spatial dimension than those in the two regions mentioned, our estimated value for radius R again appears a plausible one.

process, with our results showing that traditional, locally bounded, spillovers have an important attraction capacity over industrial firms. The principal urban centres of the region generate important agglomeration forces due to the existence of consolidated industrial clusters, as it is the case of Yecla concerning the furniture industry, or Lorca and Cartagena for the agri-food industry. However, diversity economies appear as the most salient agglomeration factor in the region, which denotes the importance of the existence of a diverse industrial environment when choosing the location of a new industrial firm. In this respect, the two urban centres with more than 100,000 inhabitants in the region, the city of Murcia and Cartagena, reveal themselves as the main destinations of industrial firms, reinforcing the result concerning the importance of diversity economies as a location factor. This finding is also reinforced by the results obtained for the variable NIND. Indeed, an important specialisation on industrial activities of the chosen municipality acts as another relevant factor of attraction for new industrial firms, so companies in this region seem to prefer locations with an important presence of industrial firms and industrial employment. In addition, the variable NSERV is not statistically significant, which seems to reflect the fact that the presence of an important specialisation in services activities and a good pool of employment in this sector of activity have a very limited role in the location choices for the industries of the region.

Qualification of the labour force in the upper levels of the education system also appears to be a very important factor for firms. Most populated municipalities are preferred to less populated ones, with this variable (TPOP) acting as a demand-side location factor. Finally, our institutional locational factor, the availability of industrial land in municipalities where the firm's plant is built, is found to be another important factor influencing location decisions, with this result reflecting the important role that public authorities could play in managing local and regional development policies by providing a suitable environment where industrial firms can start and consolidate their activities.

Extending the conditional logit by introducing space allows us to test for the influence of neighbourhood spillovers in firms' location choices. Results from estimating the spatial conditional logit model are collected in Table 2 (columns 3 and 4). In general, we observe that the results for the extended model closely follow those of the non–spatial one, except for the NSERV variable which now shows a negative sign in its coefficient, although it continues to be insignificant. Quantitatively, all coefficients appear to be highly significant, showing a reduction in their absolute values in comparison with those of the non-spatial model, except for INDSURF and DIV variables which show a slight increase in their estimated values. In this respect, including an explicit spatial component in the model would be contributing to obtain more accurate estimates of the coefficients for the specified locational factors, this being an important result of the research. As a summary, we can conclude that the spatially extended model performs well, and all of the specified locational factors appear to be playing an important role in informing the firm's choice in our empirical exercise, in this way confirming the importance given to them in the literature (Arauzo et al. 2006).

Regarding the spatial coefficient of interest δ, we obtain an estimated value of 0.83 which is highly significant. Moreover, we have tested whether the value of the spatial coefficient is above or below one, and we were unable to reject the hypothesis that it is equal to or below one, that is, $\delta \leq 1$, what reinforces our theoretically-informed perception on what this value should be (Table 2).[12] According to the theoretical model, this value implies that the characteristics of the chosen municipality appear to be more relevant than those of the neighbourhood for the decision-maker's choice, what seems to be a plausible result. In comparison with the results of Autant-Bernard (2006), and although we do not share the same methodological approach, a pseudo-δ can be inferred in her paper, for the only particular spatially lagged location factor that appears to be statistically significant, of around 0.25-0.33 for the regional case. Combining her and our results, we would infer that spillovers are more important (three times as important) at a local (municipal) level than at a regional one, which, in Autant-Bernard's own words, would add new evidence "*supporting the hypothesis of a decline of knowledge [or whatever spatial effects] diffusion over space*" (*ibid*, p. 1196). This is a pivotal result of this research because it confirms the usefulness

[12] Robustness tests are carried out along the empirical study, with all of our slightly modified specifications showing similar results.

of the parameter δ when employed as a direct measure of the empirical relevance of space in industrial location decisions.

Further analysis was carried out by computing elasticities for the estimated model.[13] Elasticities are common in economics, providing unit-free measures of the degree of responsiveness of one variable to changes in another. In our case, computed elasticities gives the percentage change in the probability of a firm locating in a given municipality as a result of a 1% increase in one of the municipality's attributes. Note that we have calculated elasticities for both the standard conditional logit (Table 3) and the spatially extended model (Table 4). A detailed analysis of the elasticities by municipalities provides us with richer information on the relevance that the different locational factors play in influencing firms' choices. Our results suggest that the most important factor at municipal level is the existence of an important stock of human capital; that is, the pool of qualified workforce. In fact, the estimated elasticity for this variable (HC) is above 2 for all the municipalities, according to the spatial conditional logit model. The second variable in terms of importance for the firm's choice is the ability to benefit from agglomeration economies, with diversity economies playing a more important role than specialisation ones.

It is worth noting that availability of industrial land (INDSURF) is also a very important location factor, particularly for firms establishing in several municipalities of the region, such as Lorca, Jumilla or Moratalla, which are rather distant from the administrative centre of the region (city of Murcia). On the other hand, the presence of a considerable number of industrial jobs in the municipality, reflecting some municipal specialisation in the industrial activities, and demand-side variables, represented by local population, turn out to be the least important factors in driving firms' choices, although the existence of a large enough local market where firms could sell their industrial products appears to be of major importance for companies located in the most populated municipalities of the region: Lorca, Cartagena and the city of Murcia, which show a value for their respective elasticities of 0.3, 0.7, and 1.0 for this factor. Comparing elasticities for

[13] Elasticity values are computed employing (evaluating) the observed value of every explanatory variable in the correspondent municipality.

the spatial and non-spatial specifications, one can see that, in general, the introduction of space results in an increase in the value of estimated elasticities for DIV and INDSUR variables, and a reduction in the value for the other elasticities, where the change in the case of the NIND variable is particularly remarkable.

Finally, we retrieved the estimated value of the probability of locating in every individual municipality of the region, and these are displayed in the last column of Tables 3 and 4. From these probabilities, and as a corollary of the research, we conclude that the main urban locations appear to maintain a higher capacity of attracting new industrial firms, with probabilities ranging from 30 per cent of the city of Murcia and 8 and 6 per cent for Yecla and Cartagena. In general, these municipalities also usually show higher elasticity values for each individual location factor included in the model.

4 Concluding remarks

By using detailed data on more than 8,000 firms located in the municipalities of the Spanish Region of Murcia, this paper is intended to improve the understanding of the role that spatial spillovers play in influencing location choices of industrial establishments. Departing from the traditional theoretical framework characterising industrial location literature, this research looks to test whether the decision-maker’s choice may be influenced not only by the characteristics of a certain location, but also by those of the surrounding or neighbouring areas, given the presence of important spatial dependence patterns at a local level. Accounting for such spatial effects has required extending the conditional logit framework by specifying a new model that relates the probabilities of locating in one municipality to a set of potential driving factors, together with the inclusion of the local spatial effects. As a novelty, we define a spatial coefficient as a synthetic measure quantifying the strength of neighbourhood effects in the firms’ choice, thus allowing for a better understanding of the role played by spatial effects at a local, sub-regional, level.

Our results are largely consistent with previous studies. Estimates of the spatial conditional logit show the important role played by local attributes, such as the existence of agglomeration economies, the presence of supply-side factors, captured by a human capital measure, and some institutional factors, such as the availability of industrial land, in increasing the attractiveness of a given location for firms. Furthermore, our findings have shown that local spatial effects are remarkably important in determining location choices, with attributes of neighbouring municipalities showing nearly the same importance as those of the chosen municipality itself for the decision-maker, confirming the need to account for such spatial effects when analysing industrial location choices. Similarly, our results have shown that local spatial spillovers are more important in influencing firms' choices than those appearing on a regional scale, again reinforcing the empirical evidence on the existence of a decline in spillovers over space. In this sense, the use of the municipality as the geographical unit of analysis has proved appropriate in order to capture spatial spillovers in discrete choice models.

Finally, our results have important implications in terms of regional policy. Firstly, they highlight the need to continue improving supply-side factors in order to push industrial development at a regional scale, showing that improving the qualifications of the labour force appears as the most salient policy a locality could pursue. Secondly, agglomeration economies and other spatial spillovers not locally-bounded continue to be first order factors influencing industrial location, so policies directed to promote spatial clustering of firms continue to be important as an instrument to consolidate industrial areas at a local level. Promoting a rich and diverse industrial environment has been equally pointed out as a relevant factor in attracting new industries. Institutional factors also appear to be important, so industrial policy at a regional and local level should be more proactive if it wants to affect location choices. And, thirdly, demand-side factors, such as the magnitude of potential demand, are shown again to be important once a certain threshold level has been exceeded. In summary, the results of the research show that this new framework of analysis for empirical studies on location choices performs remarkably well.

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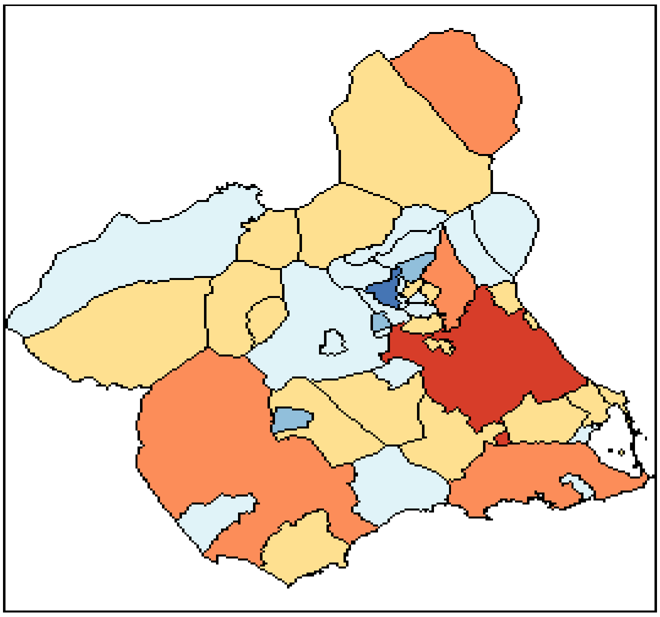
Tables and figures

Fig 1 Percentile Map on the distribution of industrial firms by municipality in the Region of Murcia (Spain)



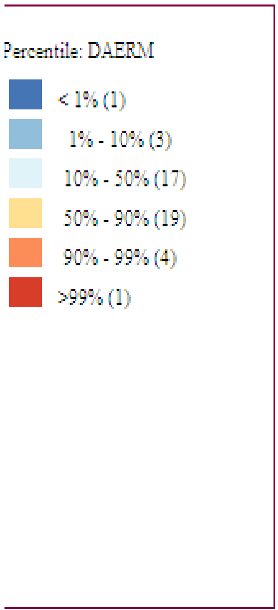


Table 1 Number of firms by sectors

Sectors	Number of firms	NACE Rev.1 classif. (R93)
FOOD, DRINKS AND TOBACCO	1500	15+16
TEXTILES	319	17(p)
CLOTHING	350	17(p)
LEATHER AND SHOES	290	18+19
WOOD AND CORK PRODUCTS	552	20 (p)+36
PRINTING, AND PUBLISHING	515	21+22 +23
CHEMICAL	332	24
RUBBER AND PLASTIC	247	25
NON METALLIC MINERALS	637	14
STEEL AND METAL PRODUCTS	1458	13+27+28
AGRICULTURAL AND INDUSTRIAL MACHINERY	611	29
OFFICE MACHINERY, ELECTRIC AND ELECTRONIC PRODUCTS	315	30+31+32+33
FURNITURES AND OTHER MANUFACTURES	1303	20(p) + 26
TOTAL	**8429**	

Source: DAERM database.

Table 2 Conditional Logit estimates (with and without space)

	Conditional Logit			Spatial Conditional Logit		
variable	coeff.		s.e.	coeff.		s.e.
LOC	0.2005	***	0.0189	0.1537	***	0.0167
DIV	0.7806	***	0.0664	0.8920	***	0.0711
HC	6.8039	***	0.2783	5.6948	***	0.2716
TPOP	0.0036	***	0.0002	0.0038	***	0.0002
NIND	1.2593	***	0.1424	0.6599	***	0.0990
NSERV	0.2546		0.1717	-0.0309		0.0773
INDSURF	0.8737	***	0.0308	1.0377	***	0.0272
δ	-		-	0.8307	***	0.0446
Log-likelihood	-25179.98			-25026.98		
Pseudo-R^2	0.2106			0.2154		
AIC	0.1358			0.1350		
LR χ^2	13433.92	***		13739.90	***	
Number of obs.	370876			370876		
χ^2 ($\delta = 1$)	-			14.4236		
($\delta = 1$) p-value	-			0.0001		
($\delta \leq 1$) p-value	-			0.9999		
($\delta \geq 1$) p-value	-			0.0001		
R (in metres)	-			43650		

(***), (**), and (*) indicates significance at the 1%, 5% and 10% level.
Source: Own elaboration based on DAERM database.

Fig 2 Grid search for radius *R* following the maximum-likelihood criterion

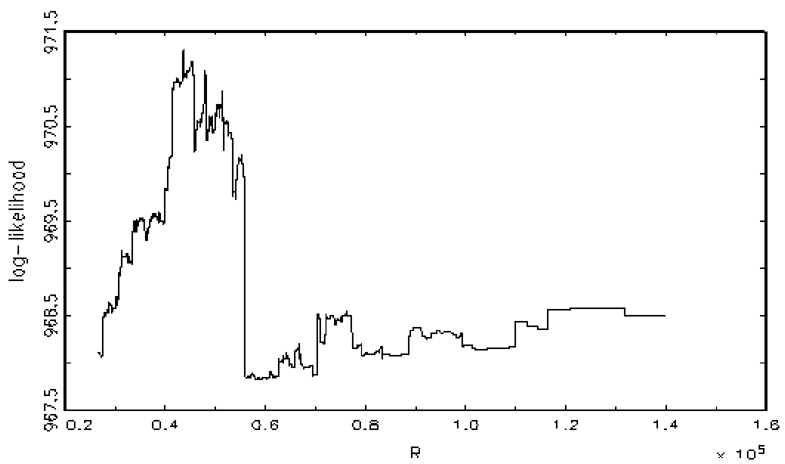


Table 3 Conditional Logit model: elasticities

Municipality (j)	Explanatory variables (X_j) LOC	DIV	HC	TPOP	NIND	NSERV	INDSURF	Prob.
ABANILLA	0.3368	0.6573	2.8063	0.0227	0.4295	0.1154	0.2054	0.0083
ABARAN	0.1202	0.5598	3.3075	0.0465	0.0872	0.1759	0.0989	0.0069
AGUILAS	0.0673	0.5176	3.6184	0.1168	0.0996	0.1319	0.2179	0.0102
ALBUDEITE	0.0728	0.4560	2.7197	0.0051	0.4517	0.0609	0.0148	0.0037
ALCANTARILLA	0.3351	0.6320	3.9319	0.1362	0.5309	0.0875	0.0136	0.0281
ALEDO	0.1825	0.0000	3.0274	0.0036	0.6469	0.0981	0.0435	0.0046
ALGUAZAS	0.4433	0.3173	3.2806	0.0295	0.5968	0.0936	0.0208	0.0103
ALHAMA	0.6740	0.3360	3.3415	0.0672	0.2557	0.1705	0.2686	0.0148
ARCHENA	0.2002	0.5203	3.7612	0.0598	0.4068	0.1175	0.0138	0.0143
BENIEL	0.3610	0.5156	3.4333	0.0363	0.3622	0.1342	0.0086	0.0111
BLANCA	0.1651	0.5529	3.1974	0.0220	0.3911	0.1022	0.0754	0.0077
BULLAS	0.2548	0.2160	3.0548	0.0430	0.1635	0.0717	0.0714	0.0040
CALASPARRA	0.3374	0.2989	2.7199	0.0361	0.5774	0.0603	0.1616	0.0056
CAMPOS DEL RIO	0.8138	0.0773	3.1479	0.0075	0.9310	0.0272	0.0405	0.0137
CARAVACA	0.3439	0.5502	3.6377	0.0874	0.6507	0.0813	0.7143	0.0483
CARTAGENA	0.1076	0.1951	3.9902	0.7120	0.6516	0.0769	0.4584	0.0597
CEHEGIN	0.3882	0.5485	3.3239	0.0556	0.6803	0.0753	0.2563	0.0188
CEUTI	0.4905	0.4763	3.9409	0.0315	0.5412	0.0629	0.0085	0.0244
CIEZA	0.1388	0.6371	3.2752	0.1247	0.1871	0.1014	0.3173	0.0103
FORTUNA	0.3565	0.6262	2.6482	0.0314	0.5843	0.0471	0.1293	0.0071
FUENTE ALAMO	0.3428	0.5371	3.1798	0.0513	0.4624	0.0732	0.2366	0.0115
JUMILLA	0.2791	0.6482	3.3654	0.0854	0.1976	0.1207	0.8283	0.0236
LA UNION	0.1280	0.6066	3.4656	0.0579	0.2993	0.0948	0.0216	0.0092
LAS TORRES	0.6178	0.4878	3.5339	0.0665	0.8148	0.0466	0.0332	0.0259
LIBRILLA	0.2425	0.5400	2.5435	0.0152	0.5904	0.1014	0.0496	0.0050
LORCA	0.1767	0.6364	3.2818	0.3086	0.2287	0.1205	1.3841	0.0542
LORQUI	0.3396	0.6307	3.3279	0.0233	0.5285	0.1077	0.0138	0.0127
LOS ALCAZARES	0.0752	0.5769	3.9380	0.0480	0.1358	0.1648	0.0173	0.0125
MAZARRON	0.0527	0.5874	3.4644	0.1108	0.0585	0.1209	0.2762	0.0092
MOLINA	0.3037	0.6432	4.0433	0.2000	0.4984	0.1107	0.1426	0.0403
MORATALLA	0.4099	0.4428	2.8927	0.0298	0.8785	0.0266	0.8153	0.0228
MULA	0.3115	0.3116	3.4656	0.0582	0.4594	0.0712	0.5447	0.0167
MURCIA	0.0832	0.4731	3.2862	1.0432	0.1358	0.1204	0.5335	0.3108
PLIEGO	0.1390	0.3461	2.6446	0.0134	0.0219	0.1447	0.0253	0.0023
PTO LUMBRERAS	0.1059	0.6458	3.1490	0.0465	0.1335	0.1166	0.1259	0.0064
RICOTE	0.1536	0.4355	2.9494	0.0054	0.1568	0.0127	0.0766	0.0037
SAN JAVIER	0.0757	0.6167	4.1262	0.0985	0.0935	0.1517	0.0644	0.0168
SAN PEDRO	0.1030	0.5333	3.4407	0.0764	0.1404	0.1609	0.0191	0.0075
SANTOMERA	0.2255	0.6744	3.6588	0.0497	0.3077	0.1563	0.0379	0.0147
TORRE-PACHECO	0.1260	0.6312	3.4728	0.1014	0.1193	0.1052	0.1635	0.0097
TOTANA	0.2272	0.6054	3.0009	0.1022	0.3170	0.1071	0.2503	0.0086
ULEA	0.3073	0.0000	3.4147	0.0036	0.0534	0.1456	0.0348	0.0044
VILLANUEVA	0.0607	0.0000	3.7458	0.0069	0.0256	0.1190	0.0113	0.0044
YECLA	0.6703	0.3181	3.6592	0.1166	0.8229	0.0601	0.4979	0.0550

Elasticities are computed as: $\frac{\partial P_j}{\partial X_{m,j}} \frac{X_{m,j}}{P_j} = \left(1 - P_j\right) \beta_m X_{m,j}$.

Table 4 Spatial Conditional Logit model: elasticities

	Explanatory variables (X_j)							
Municipality (j)	LOC	DIV	HC	TPOP	NIND	NSERV	INDSURF	Prob.
ABANILLA	0.2579	0.7505	2.3465	0.0237	0.2250	-0.0138	0.2437	0.0091
ABARAN	0.0922	0.6400	2.7696	0.0487	0.0457	-0.0210	0.1175	0.0063
AGUILAS	0.0515	0.5902	3.0218	0.1219	0.0521	-0.0157	0.2583	0.0123
ALBUDEITE	0.0558	0.5211	2.2759	0.0053	0.2368	-0.0073	0.0176	0.0037
ALCANTARILLA	0.2575	0.7240	3.2992	0.1429	0.2791	-0.0105	0.0162	0.0255
ALEDO	0.1400	0.0000	2.5352	0.0038	0.3394	-0.0117	0.0517	0.0039
ALGUAZAS	0.3398	0.3628	2.7466	0.0308	0.3131	-0.0112	0.0247	0.0099
ALHAMA	0.5183	0.3853	2.8061	0.0706	0.1345	-0.0205	0.3201	0.0114
ARCHENA	0.1540	0.5969	3.1599	0.0628	0.2141	-0.0141	0.0164	0.0104
BENIEL	0.2765	0.5889	2.8716	0.0379	0.1898	-0.0160	0.0103	0.0117
BLANCA	0.1267	0.6328	2.6802	0.0230	0.2054	-0.0122	0.0897	0.0061
BULLAS	0.1952	0.2468	2.5561	0.0450	0.0857	-0.0086	0.0847	0.0042
CALASPARRA	0.2587	0.3417	2.2772	0.0378	0.3029	-0.0072	0.1920	0.0051
CAMPOS DEL RIO	0.6273	0.0889	2.6500	0.0079	0.4910	-0.0033	0.0484	0.0079
CARAVACA	0.2654	0.6330	3.0654	0.0921	0.3436	-0.0098	0.8542	0.0417
CARTAGENA	0.0827	0.2237	3.3505	0.7476	0.3428	-0.0092	0.5463	0.0565
CEHEGIN	0.2985	0.6290	2.7915	0.0584	0.3579	-0.0090	0.3055	0.0154
CEUTI	0.3784	0.5479	3.3200	0.0332	0.2856	-0.0076	0.0102	0.0179
CIEZA	0.1063	0.7279	2.7407	0.1304	0.0981	-0.0121	0.3769	0.0104
FORTUNA	0.2731	0.7153	2.2151	0.0328	0.3062	-0.0056	0.1534	0.0076
FUENTE ALAMO	0.2622	0.6126	2.6562	0.0536	0.2420	-0.0087	0.2805	0.0134
JUMILLA	0.2139	0.7410	2.8175	0.0894	0.1036	-0.0144	0.9841	0.0233
LA UNION	0.0977	0.6901	2.8874	0.0603	0.1562	-0.0113	0.0256	0.0136
LAS TORRES	0.4763	0.5609	2.9759	0.0700	0.4298	-0.0056	0.0397	0.0198
LIBRILLA	0.1858	0.6171	2.1285	0.0159	0.3095	-0.0121	0.0589	0.0050
LORCA	0.1362	0.7317	2.7631	0.3250	0.1206	-0.0145	1.6538	0.0485
LORQUI	0.2604	0.7212	2.7870	0.0244	0.2773	-0.0129	0.0164	0.0120
LOS ALCAZARES	0.0574	0.6572	3.2855	0.0501	0.0710	-0.0196	0.0204	0.0155
MAZARRON	0.0403	0.6690	2.8897	0.1155	0.0306	-0.0144	0.3269	0.0125
MOLINA	0.2345	0.7406	3.4094	0.2109	0.2633	-0.0133	0.1706	0.0330
MORATALLA	0.3136	0.5052	2.4169	0.0311	0.4598	-0.0032	0.9667	0.0245
MULA	0.2397	0.3575	2.9119	0.0611	0.2418	-0.0085	0.6495	0.0127
MURCIA	0.0636	0.5392	2.7428	1.0888	0.0710	-0.0144	0.6319	0.3127
PLIEGO	0.1065	0.3953	2.2122	0.0140	0.0115	-0.0173	0.0300	0.0028
PTO LUMBRERAS	0.0807	0.7341	2.6215	0.0484	0.0696	-0.0139	0.1487	0.0116
RICOTE	0.1177	0.4976	2.4680	0.0057	0.0822	-0.0015	0.0910	0.0038
SAN JAVIER	0.0579	0.7031	3.4450	0.1028	0.0489	-0.0181	0.0763	0.0191
SAN PEDRO	0.0786	0.6073	2.8693	0.0797	0.0733	-0.0192	0.0226	0.0110
SANTOMERA	0.1728	0.7706	3.0616	0.0520	0.1613	-0.0187	0.0450	0.0148
TORRE-PACHECO	0.0960	0.7174	2.8906	0.1055	0.0622	-0.0125	0.1932	0.0150
TOTANA	0.1741	0.6915	2.5104	0.1069	0.1661	-0.0128	0.2972	0.0090
ULEA	0.2359	0.0000	2.8623	0.0038	0.0280	-0.0174	0.0414	0.0028
VILLANUEVA	0.0465	0.0000	3.1396	0.0072	0.0134	-0.0142	0.0135	0.0029
YECLA	0.4981	0.3525	2.9695	0.1184	0.4184	-0.0070	0.5734	0.0836

Elasticities are computed as: $\frac{\partial P_j}{\partial X_{m,j}} \frac{X_{m,j}}{P_j} = \left(1 - P_j\right) \beta_m X_{m,j}$.

Appendix

Table A.1 Definition of the explanatory variables

Variable	Definition	Source
LOC	Industrial specialisation index computed as $\dfrac{e_j^s \Big/ \sum_{s=1}^{S} e_j^s}{\sum_{j=1}^{J} e_j^s \Big/ \sum_{s=1}^{S}\sum_{j=1}^{J} e_j^s}$ where e_j^s denotes sector *s* employment in the municipality *j*	DAERM database (Regional Statistical Office of Murcia).
DIV	Diversification index computed as $1-\sum_{r\in I}\left(e_j^r \Big/ \sum_{r\in I} e_j^r\right)^2$ where e_j^r denotes industrial employment in sector *r* and municipality *j* over total industrial employment in the municipality *j*. The index takes values in the interval (0,1), where 0 indicates the lowest degree of diversification while 1 is associated to the highest degree of diversification	DAERM database (Regional Statistical Office of Murcia).
HC	Percentage of labour force with secondary and tertiary levels of education by municipality	Population Census, Spanish National Statistics Institute (INE)
TPOP	Total population by municipality	Population Census, Spanish National Statistics Institute (INE)
NIND	Share of local industrial employment over regional industrial employment	DAERM database (Regional Statistical Office of Murcia).
NSERV	Share of local services employment over regional services employment	Regional Accounts (CRE), Spanish National Statistics Institute (INE)
INDSURF	Industrial land availability by municipality	sueloindustrial-murcia.com/index.htm