Spatial location patterns of Spanish manufacturing firms*

José M. Albert, Marta R. Casanova and Vicente Orts†

Abstract

In this paper, we evaluate the spatial location patterns of manufacturing firms and we assess the different tendencies to cluster in each industry. To do this, we use a distance-based method, more specifically Ripley's *K* function, which allows us to treat space as continuous by counting the average number of neighbours of each firm within a circle of a given radius. We apply this method to Spanish manufacturing sectors at a two-digit level. The results are sensitive to the benchmark employed; in fact, if we use 'complete spatial randomness' as a benchmark, every sector analysed presents a significant concentration whatever the length of the radius considered. However, if we use the locations of all manufacturing firms as our benchmark, we find different patterns of location, with dispersion in some sectors and concentration in others, finding also differences in the spatial scale at which clustering occurs.

Keywords: distance-based method, Ripley's *K* function, Spanish manufacturing firms, spatial location patterns.

JEL classification: C15, C40, C60, R12.

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1. Introduction

Economic activity is distributed across space heterogeneously and this distribution does not necessarily take into account administrative frontiers or country boundaries. Some traditional and well-known examples of this geographic concentration are high-tech firms in Silicon Valley, the auto industry in Detroit or the carpet industry in Dalton (USA) and, going back further in time, the textile industry in Lancashire (UK). In Spain, the tile industry in Castellón or the leather and footwear industry in Elche are also good examples of this tendency towards the geographic concentration of economic activity.

Heterogeneity of the spatial distribution of activity can be caused by multiple and very different factors, and a substantial body of literature has focused on this topic, the result being significant advances in the identification of the forces and factors that determine the choice of location by firms. Thus, the pioneering work by Marshall (1890) put special emphasis on the role of specialised local markets, positive externalities and linkages, as sources of agglomeration. A century later, the 'new economic geography', initiated by Krugman (1991a, b), highlighted the role of economies of scale and transport costs as the main agglomeration forces, which interact with the dispersion forces, immobile factors and product market competition to determine the location of economic activity.[1]

However, economists are not only concerned about the determinants of geographic concentration, but also how to measure and characterise the patterns of geographic concentration of firms and industries in space; this paper deals with this second aspect. In fact, its main objective will be to measure the spatial location patterns of Spanish manufacturing sectors by improving the application of some recent methods developed to assess the geographic distribution of economic activity.

[1] For further details see Ottaviano and Puga (1998), Fujita et al. (1999), Puga (1999, 2002), Overman et al. (2003), Venables (1995, 2006), Ottaviano and Thisse (2004) Fujita and Thisse (2009) or Redding (2009).

Many techniques have been employed in the literature to assess geographic concentration, but the indices of Gini or Ellison and Glaeser (1997) have been the most recently used. Krugman (1991a), Brülhart (2001) or Amiti (1997), among others, used the Gini index to measure how economic activity was distributed across space. Nonetheless, this index cannot distinguish whether concentration of activity is due to a few huge firms in a specific area or due to many small firms in the same specific area. Ellison and Glaeser (1997) tried to solve this shortcoming by comparing concentration resulting from a random and independent location of firms with the real geographic concentration of an industry, now taking into account the size of firms. Thus, this index allows us to compare concentration between industries or the concentration of a given industry in different countries. Indeed many authors, such as Devereux et al. (2004), Rosenthal and Strange (2001) or Maurel and Sédillot (1999), have used it to measure geographic concentration of activity in their respective countries, i.e. UK, USA and France.

In Spain, many authors are also interested in this topic, the most notable being Callejón (1997), Viladecans (2001), Alonso-Villar et al. (2003, 2004) or Paluzie et al. (2004). From a different perspective, other papers have also used this kind of indices in the analysis of the determinants of industrial localization in Spain, as is the case of Paluzie et al. (2001) or Tirado et al. (2002). It should be borne in mind that most of these Spanish studies use the Gini index to measure geographic concentration of activity. Callejón (1997), however, uses the Ellison and Glaeser index, Alonso-Villar et al. (2003) introduce the index proposed by Maurel and Sédillot (1999) into their analysis and Viladecans (2001) uses an econometric spatial index, called Moran's I statistic of spatial association.

These methods, which have been used until now in Spain and in other countries to measure geographic distribution of activity, have a common drawback: they *treat space as being discrete*. They restrict the spatial distribution to just *one scale* and analyse the distribution of activity over discrete geographic units, which do not necessarily coincide with the relevant scale from the economic point of view. In this way, the spatial scale chosen is a key decision that may alter the results and conclusions reached. For instance, Viladecans (2001) uses more than one geographic level in her analysis,[2] as do Alonso-Villar et al. (2003),[3] to determine the most suitable administrative unit in each analysis.

This paper avoids the inconvenience of *geographic scale*, as Marcon and Puech (2003a) or Duranton and Overman (2005) did. In this way, we will *treat space as continuous* in order to obtain a proper analysis of spatial location patterns, instead of sticking to administrative scale data. To do this, we employ a *distance-based method* that satisfies the essential requirements and achieves our aim by enabling us to know and to compare the concentration intensity for every spatial scale. To consider space as continuous, a suitable dataset is also necessary.

Like Marcon and Puech (2003a), the distance-based method we are going to use to measure the spatial distribution of activity in Spain is Ripley's *K* function,[4] which offers important advantages over traditional concentration indices. Indeed, by means of this method, we can know whether concentration exists, what its intensity is and at what distance, or spatial scale, its highest level is obtained.[5] Furthermore, in contrast with Marcon and Puech (2003a), and like Duranton and Overman (2005) did, we control for the general tendency of the manufacturing industry to agglomerate and for industrial concentration of each sector.

In addition, we must emphasise other aspect that differentiate our empirical analysis others: our location of firms is very accurate, because we know the geographic coordinates (longitude and latitude) of every establishment. Thus, we

[2] She uses the municipal and provincial level, corresponding to NUTS 5 and 3.
[3] They use the provincial and regional level, corresponding to NUTS 3 and 2.
[4] For further details, see Ripley (1976, 1977, 1979).
[5] Marcon and Puech (2003) have previously used this concentration index, in France, to measure the spatial distribution of economic activity.

employ these coordinates to situate each firm as a dot on the map, without taking administrative borders into account.[6]

The remainder of the paper is organised as follows. In Section 2, we outline the methodology employed and the key improvements incorporated into our application. In Section 3, we describe our data set. In Section 4, we present and discuss the main results achieved, comparing them with those from other authors. Finally, Section 5 contains the most important conclusions reached.

2. Methodology

Ripley's *K* function, *K*(*r*), is a distance-based method that measures concentration by counting the average number of neighbours each firm has within a circle of a given radius, 'neighbours' being understood to mean all firms situated at a distance equal to or lower than the radius (*r*). From here on, firms will be treated as points.

The *K*(*r*) function describes characteristics of the point patterns at many and different scales simultaneously, depending on the value of "*r*" we take into account, that is,

$$K(r) = \frac{1}{\lambda N} \sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} w_{ij} I(d_{ij})$$

$$I(d_{ij}) = \begin{cases} 1, & d_{ij} \leq r \\ 0, & d_{ij} > r \end{cases}$$

where d_{ij} is the distance between the ith and jth firms; *I*(*x*) is the indicator function; *N* is the total number of points observed in the area of the study region; $\lambda = N/A$ represents its density, *A* being a rectangular area covering the study region; and w_{ij}

[6] Until now most of studies have used the postcodes of the manufacturing firms and the geographic coordinates associated with each postcode to locate them in space. See, for example, Marcon and Puech (2003) and Duranton and Overman (2005).

is the weighting factor to correct for border effects.[7] The indicator function, $I(d_{ij})$, takes a value of 1 if the distance between the i[th] and j[th] firms is lower than r, or 0 otherwise, and w_{ij} will be equal to the area of the circle divided by the intersection between the area of the circle and the area of study.

Finally, using the definition of λ, the $K(r)$ function can be rewritten as:

$$K(r)=\frac{A}{N^2}\sum_{i=1}^{N}\sum_{j=1,i\neq j}^{N}w_{ij}I(d_{ij})$$

Therefore, the $K(r)$ function shows the average number of neighbours in an area of radius (r), divided by the density of the whole study region (λ).

The next step in the evaluation of the location patterns of economic activity is to determine the null hypothesis and compare it with our results. The null hypothesis is usually a kind of randomly distributed set of locations in the area of study. Thus, if firms were located in the study area random and independently from each other, we would have a location pattern known as C*omplete Spatial Randomness* (*CSR*). This is our first benchmark and, as long as we assume CSR, the K function will be equal to πr^2.

Consequently, we define $M_{CSR}(r)$ as the value that quantifies the difference between the empirical K value of the real point pattern of each sector and the theoretical K value,[8] that is:

$$M_{CSR}(r)=K(r)-\pi r^2$$

If the empirical K value, $K(r)$, is higher than the theoretical K value, πr^2, this indicates concentration of our point pattern distribution, since the real density is

[7] These border-effect corrections should be incorporated to avoid artificial decreases in $K(r)$ when r increases, because the increase in the area of the circle under consideration is not followed by the increase of firms (outside the study area there are no firms).
[8] Marcon and Puech (2003) used the normalised function, $L(r)$, because they considered that '*a practical limitation of Ripley's K function is the need to compare any value to* πr^2. However, we do this directly thanks to the statistical software employed.

greater than that of the benchmark. Lower values indicate dispersion and if $K(r)$ is equal to πr^2, then this means that our points are independently distributed.

Figures 1 and 2 show two spatial distributions of points, both with the same number of points (100) inside the same area. However, the points in Figure 1 are distributed at random and independently from each other, while the points in Figure 2 show some tendency to cluster.

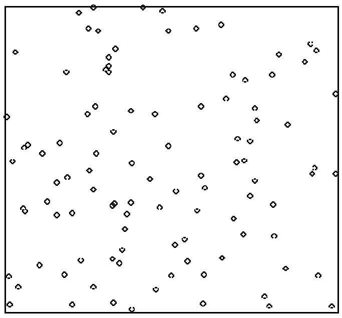


Figure 1. Independent distribution.

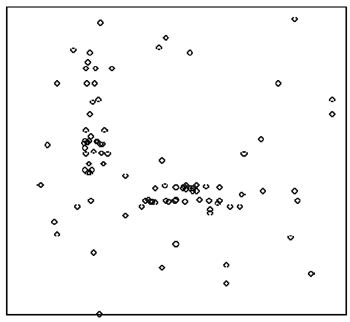


Figure 2. Concentrated distribution.

Figures 3 and 4 show the empirical and theoretical K functions and the corresponding M_{CSR} functions of the point patterns that appeared in Figures 1 and 2.

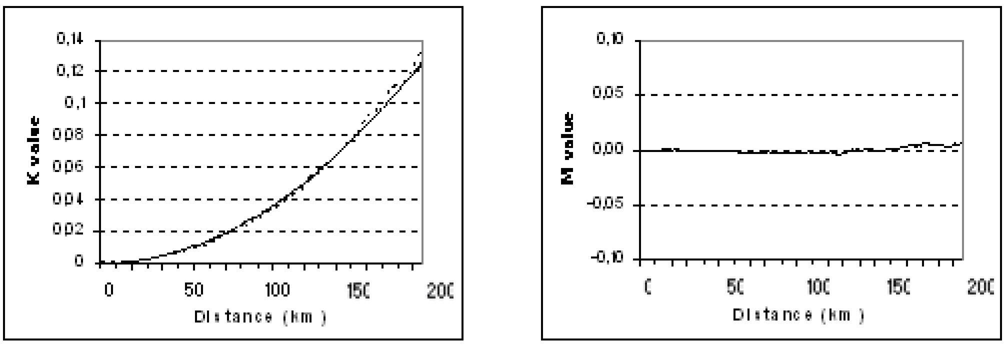


Figure 3. Ripley's K function (theoretical and empirical) and M function corresponding to the point pattern from Figure 1.

As we can see, on the left-hand side of Figure 3 there are two lines. The dashed line represents the empirical K value, that is to say, the K value of the observed point pattern in Figure 1, and the continuous line takes a value of πr^2, since this represents the CSR benchmark. We can observe that the values of these two lines are almost the same, no matter what radius we take into account ($K(r) \approx \pi r^2$). The right-hand graph in Figure 3 shows the value of the M_{CSR} function. Consequently, it can be seen that an independent and random distribution of points produces an almost flat *M* curve, with a value of around zero.

The graphs in Figure 4 give us the same information as the previous ones, but refer to the spatial distribution of the points in Figure 2. Here, in the left-hand graph we can observe that $K(r) > \pi r^2$ at all distances of "*r*" considered, which means that the point pattern in Figure 2 presents concentration at all distances. Moreover, from the M_{CSR} curve we can determine the distance at which the highest level of concentration is reached. This curve also indicates whether the point pattern observed is concentrated or dispersed relative to the benchmark under consideration, depending on its positive or negative value. Therefore, the M_{CSR} curve provides concise information with which to analyse different location patterns and we will use this function throughout the paper to analyse the spatial location patterns of Spanish manufacturing firms.

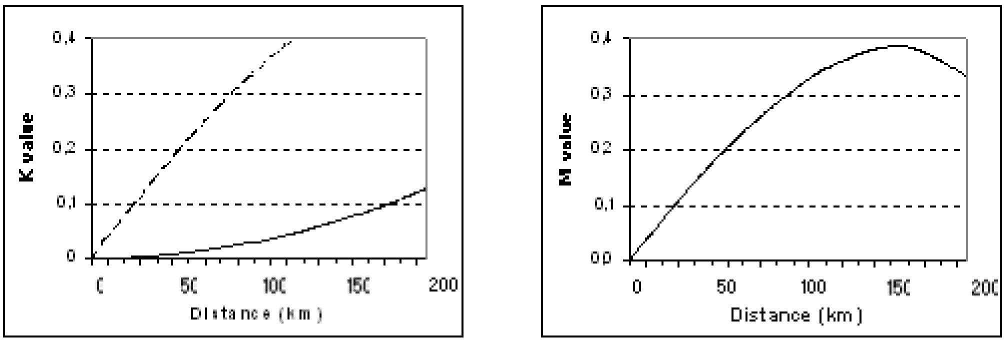


Figure 4. Ripley's *K* function (theoretical and empirical) and *M* function corresponding to the point pattern from Figure 2.

In actual fact, considering firms to be randomly and independently distributed from each other within a particular area is not completely correct because economic activity cannot be located in a random and independent way and the results are sensitive to the specific area considered. Economic activities are spatially concentrated for other reasons, very different to economic factors, for example because of dissimilarities in such natural features as mountains, rivers or harbours, that is, 'first nature'. Additionally, with CSR as our benchmark we cannot isolate the idiosyncratic tendency of each sector to locate itself in accordance with the general tendency of manufacturing firms to agglomerate.

Consequently, in the second scenario, we use the whole of manufacturing as a benchmark, thus minimizing the aforementioned drawbacks. Indeed, we can compare the spatial distribution of each sector with the overall tendency of manufacturing industry to agglomerate, that is:

$$M_{TM}(r) = K(r) - K_{TM}(r)$$

Here, $M_{TM}(r)$ is the difference between the K-value of each sector under consideration and the K-value of the total manufacturing at radius r. Localization or dispersion will appear within a particular sector depending on whether its K-value is higher or lower than K-value of the total manufacturing. In such a case, our claim is that this sector is concentrated or dispersed relative to the whole of the manufacturing industry.

Now, to evaluate the statistical significance of departures from randomness in a robust way, we should construct a confidence interval for M_{CSR} and M_{TM}. The traditional technique used to construct this confidence interval is the Monte Carlo method, which involves generating a large number of independent random simulations. It should be noted that the construction of the confidence interval will be different in the two scenarios. In the first scenario, we simulate Poisson patterns with the same number of points as in the real distribution of each sector and then locate them randomly within the area of study. In the second scenario, we also simulate random distributions with the same number of firms as in each of the sectors under consideration, but this time the location of these hypothetical firms is restricted to the sites where we can currently find firms from the whole manufacturing sector.[9] Both scenarios are generated by running 100 simulations

[9] This procedure minimizes again the shortcomings associated to the specificity of considered area.

and both allow us to reject the non-significant values. A confidence interval of 95% was utilised. In this way, the construction of the confidence interval allows us to assess the significance of departures from randomness and to control for industrial concentration.

Finally, it must be emphasised that, to the best of our knowledge, only Marcon and Puech (2003a) and Duranton and Overman (2005) have used distance-based methods to assess the geographical concentration of activity. The methodology of both tests is similar, but not identical, and we can find some differences if we analyse them in depth.

On the one hand, Duranton and Overman (2005) emphasised that their test fulfils all the five requirements that any measure of concentration should satisfy.[10] However, Duranton and Overman's method has a disadvantage with regard to Ripley's K function, that is to say, it is not possible to quantify the concentration or dispersion but only detect the proportion of sectors that are concentrated.

On the other hand, if we revise Marcon and Puech (2003a), we can see that their application of the K function, like our M_{CSR} function, is very sensitive to the study area considered[11] and does not satisfy two of the five above-mentioned requirements, since it does not control for the overall tendency of manufacturing firms to agglomerate or for industrial concentration.

Now, on examining the properties of our measure of concentration after improving the benchmark employed and making more robust the construction of the confidence interval, that is, the M_{TM} function, it can be observed that fulfils all the five requirements established by Duranton and Overman and allows us to obtain a measure that quantifies the concentration or dispersion of all our point

[10] As underlined by Duranton and Overman (2005), (1) it is comparable across industries, (2) controls for the overall agglomeration of manufacturing, (3) controls for industrial concentration, (4) is unbiased with respect to scale and aggregation, and (5) gives an indication of the significance of the results.

[11] Marcon and Puech (2003) restricted their area of study and did not analyse the whole of France, but instead an industrial area of 40 x 40 km around Paris and a larger rectangular area of France measuring 550 x 630 km.

patterns, thus minimizing the drawbacks associated to the use of rectangular areas in the analysis.

Obviously, our concentration measure based on Ripley's K function is comparable across sectors. Additionally, we control for the overall agglomeration of manufacturing by considering the whole set of manufacturing firms as our benchmark and, when constructing the confidence interval, by randomly locating the firms across the set of locations of all the manufacturing firms. The third requirement, control for industrial concentration, is satisfied by considering hypothetical sectors with the same number of firms as in each existing sector. Fourth, as we use a continuous distance method to measure spatial concentration and not an administrative scale, information about characteristic features of the patterns of localization at different scales is known and our test is unbiased with respect to scale and aggregation. Lastly, statistical significance is also satisfied, since the confidence interval allows us to know whether the observed distribution is significantly different from conditional randomness. In this case, randomness is conditioned to the industrial concentration of each sector and to the location of the overall manufacturing.

3. Data

Our empirical analysis uses current establishment level data, for the year 2007, from the Analysis System of Iberian Balances database,[12] which contains detailed information about Spanish and Portuguese companies. We restrict our database to Spanish manufacturing establishments, using the National Classification of Economic Activities[13] and analysing sectors at the two-digit level. Furthermore, we add another two requirements to our database. First, we ensure that our database contains only Spanish manufacturing firms on the peninsula, without including firms from the Canary and Balearic Islands, Ceuta and Melilla. Second,

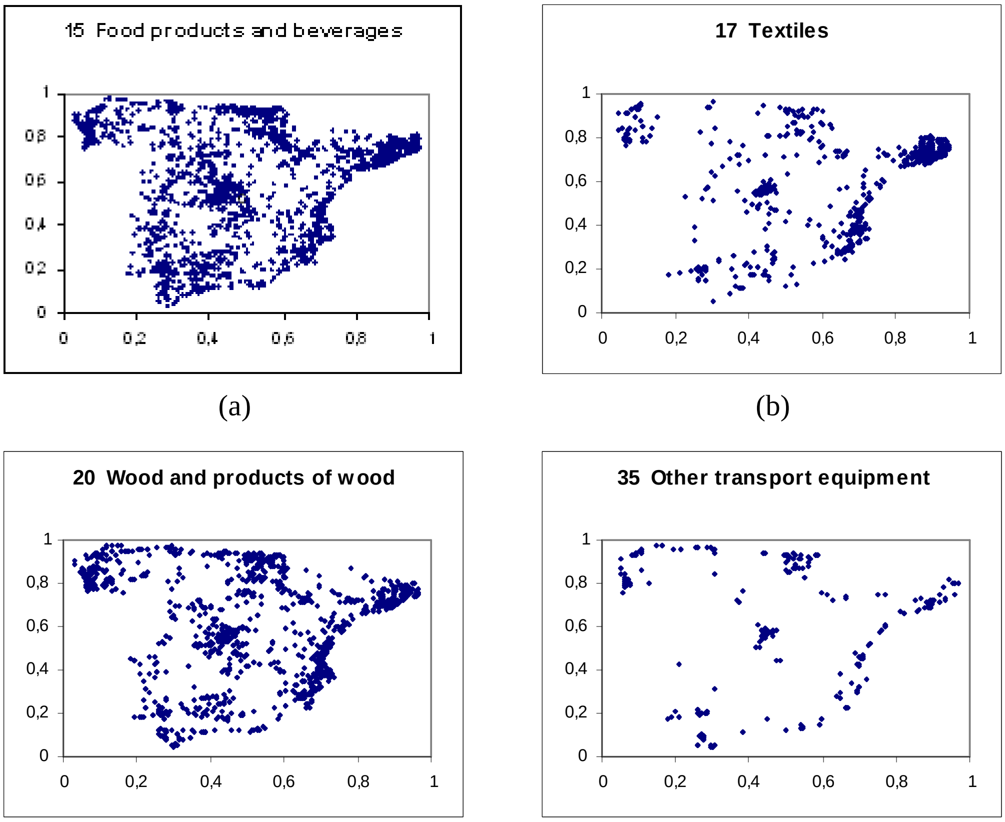
[12] SABI
[13] NACE 93 - Rev. 1

we restrict our analysis just to firms employing at least ten workers. Finally, once these requirements have been applied, our database contains exactly 43,087 firms.

At this point the comparison between our restriction, related to the number of employees, and Marcon and Puech (2003)'s restriction must be considered. In fact, they used French manufacturing firms employing at least twenty workers. This difference, concerning the number of employees, is due to the fact that SMEs (small and medium-sized enterprises) are predominant in Spain. Consequently, too many firms would be left out if we only considered those with twenty or more than twenty workers, as Marcon and Puech did.

Spanish manufacturing activities are classified into 23 sectors according to 'NACE 93 - Rev. 1' and these are as follows: (15) Food products and beverages, (16) Tobacco products, (17) Textiles, (18) Wearing apparel and dressing, (19) Tanning and dressing of leather, (20) Wood and products of wood, (21) Pulp, paper and paper products, (22) Publishing, printing and recorded media, (23) Coke, refined petroleum products, (24) Chemical and chemical products, (25) Rubber and plastic products, (26) Other non-metallic mineral products, (27) Basic metals, (28) Fabricated metal products, (29) Other machinery and equipment, (30) Office machinery and computers, (31) Electrical machinery, (32) Radio, televisions and other appliances, (33) Instruments, (34) Motor vehicles and trailers, (35) Other transport equipment, (36) Furniture and other products, (37) Recycling.

Table A1, situated in *Appendix 1*, shows us a brief descriptive analysis of the above-mentioned sectors including additional information, such as the number of firms, the number of employees, or the technological intensity of each one. Thus, as we can see in this table, there are great differences in the number of firms, depending on the sector we are referring to. Hence, three of the twenty-three sectors considered (16, 23 and 30) will not be analysed because they are too small as far as their number of establishments is concerned.



(a) (b) (c) (d)

Figure 5. Maps of spatial distribution of firms.

Figure 5 shows the spatial distribution of four Spanish manufacturing sectors (15, 17, 20 and 35). Here, each dot corresponds to an establishment and we can see that there are great differences in the spatial distributions of these sectors.

We know the *precise location* of every establishment through its geographic coordinates (longitude and latitude), which enables us to minimise the margin of error in each case.[14] These geographic coordinates are transformed into UTM[15] coordinates, or flat coordinates, as they are also called. This transformation was carried out by means of the method proposed by Morton (2003). This procedure converts latitude and longitude coordinates into Easting and Northing coordinates,

[14] Marcon and Puech (2003) and Duranton and Overman (2005) only know the postcode of each manufacturing firm and thus obtain a location error of between 100 m and about 2 km. However, if we had used the Spanish postcodes to locate the firms, our margin of error would have been higher, since our postcodes cover larger areas than those from the United Kingdom or France.

[15] Universal Transverse Mercator.

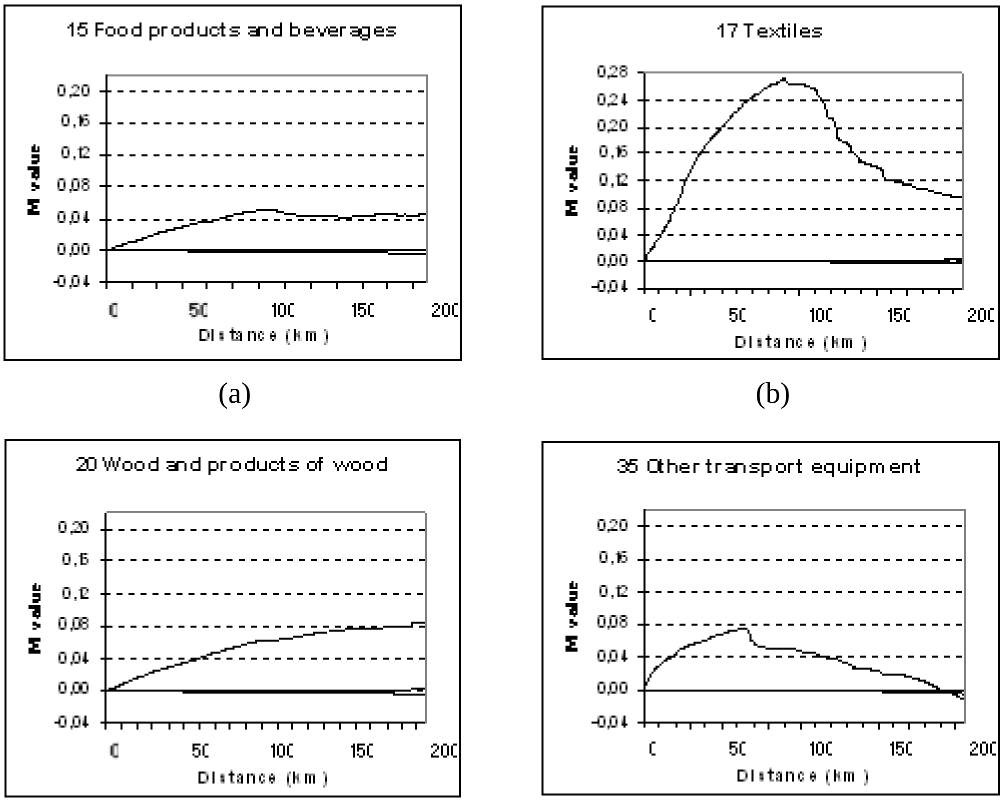
on a Transverse Mercator projection, the UTM coordinates being expressed in metres. We should highlight the fact that the construction of this system allowed us to move away from the Equator with hardly any distortions, because any point is a long way away from the central meridian of its zone.

4. Empirical Results and Discussion

In the exposition of the methodology above, we have differentiated between two scenarios. Consequently, this sequence will be the same in the discussion of our results, that is to say, first we will analyse the results coming from the '*CSR* benchmark' and, after that, those coming from the '*TM* benchmark'.[16]

In Figure 6 the M_{CSR} curves of the four sectors presented earlier (15, 17, 20 and 35) have been plotted along with their corresponding confidence intervals.[17] On observing them more closely, we can see different location patterns among these sectors. For example, the textile sector (Figure 6b) presents a higher level of concentration than the rest of the sectors. The spatial scale at which the level of maximum concentration is reached in each sector differs from one to another. In fact, as we can see, sector 35 (Figure 6d) reaches its maximum concentration peak at a lower distance than the other sectors. However, the location patterns in Figures 6b and 6d are similar to each other and different from the other two sectors, since they present an initial increase in the activity concentration, reach a maximum peak and then decrease when the length of the radius becomes higher. If we examine the confidence intervals, we can observe that these are very narrow. This is due to the way they are constructed, since the difference between the Poisson simulations and the theoretical K-value is almost zero for every r considered.

[16] We used the free statistical software 'R' to conduct our research. This software is downloadable from the following website: http://www.r-project.org/.
[17] It should be noted that all the sectors that were analysed appear together in *Appendix 2*.



(a) (b) (c) (d)

Figure 6. Spatial location patterns (M_{CSR}).

Although only four sectors appear illustrated in Figure 6, Table 1 summarises the results obtained from computing the M_{CSR} function for each sector.

INSERT TABLE 1 ABOUT HERE

First, we must focus on the second and third column in Table 1. By so doing, we can see that every Spanish manufacturing sector analysed, except for (35) ‘Other transport equipment’, presents concentration relative to complete spatial randomness, whatever the distance of “*r*” we consider.

Second, we should pay attention to the *intensity* reached by the different sectors, that is to say, we should point out which are the most and the least concentrated manufacturing sectors in Spain. Thus, the Spanish manufacturing sectors that reach the highest level of concentration are, in the following order,

(19) Tanning and dressing of leather, (17) Textiles, (32) Radio, televisions & other appliances, (33) Instruments, (22) Publishing, printing and recorded media, (24) Chemical and chemical products, and (31) Electrical machinery. In contrast, the sectors with the lowest levels of concentration are (15) Food products and beverages, (20) Wood and products of wood, (26) Other non-metallic mineral products, and (35) Other transport equipment.

Third, we should evaluate the *persistence* of this concentration in space, in other words, the spatial scale dimensions of the cluster. If we pay attention to this characteristic of spatial distribution, we can find two clearly differentiated types of sectors, called 1 or 2 depending on the characteristic features of their location patterns.[18] 'Type 1' sectors present, initially, an increase in the concentration of activity that reaches an absolute maximum point, or peak, and then they decrease as the length of the radius becomes higher. We should add that, although the spatial distribution of each of these sectors is similar to the others, the intensity and the distance at which the maximum concentration is reached may be different. Most of the Spanish manufacturing sectors belong to this 'Type 1' of location patterns[19] and the textile sector is a clear example (see Figure 6b).

Just six sectors, however, belong to 'Type 2' (15, 18, 19, 20, 26 and 36). These sectors keep a constant or growing concentration, whatever the value of "*r*" considered, without reaching an absolute maximum peak. In this second kind of sectors, we assume that this maximum peak will be reached at a value of the radius higher than 200 km (see Figure 6c).

Last but not least, the *distance* (*r*-value) at which the highest concentration is reached, or in other words the size of the cluster, is an important point to be analysed. In fact, this distance may be altered by the scope of the agglomerative forces that act in and characterise each sector. Therefore, the intensity and the distance at which the highest concentration is reached are distinctive of each

[18] We can find this information in the sixth column of Table 1, 'Type of cluster'.
[19] Sectors 17, 21, 22, 24, 25, 27, 28, 29, 31, 32, 33, 34, 35 and 37.

sector and differ from one to another. In other words, each Spanish manufacturing sector presents different location patterns, although certain regularities can be found between them.

For example, paying attention to the spatial scale at which the cluster is produced, it can be observed that this distance is very high in all sectors and in some cases coincides. As we can see in the fifth column of Table 1, nine of the twenty sectors analysed obtain their maximum concentration peak at a distance of between 85 and 91 km.[20] Thus, it is clear that a common behaviour exists in the distance at which the maximum concentration appears, thereby indicating the existence of some regularity that affects all sectors. Good candidates to explain this fact are the agglomerative forces associated to the ‘First Nature’ or the overall tendency for economic activity to agglomerate. Of course, when we use a random and independent distribution of firms as our benchmark (*CSR* benchmark), we do not take into account the ‘first nature’ or the general tendency of manufacturing industry to agglomerate, and a regularity that is non-attributable to specific economic factors in each sector is detected.

In order to correct this shortcoming of our first benchmark, we consider a different one and, as explained in the methodology, this second benchmark is constructed taking into account the location of overall manufacturing. The results of this second analysis are summarised in Table 2. Figure 7 shows the M_{TM} curves of the four sectors presented earlier (15, 17, 20 and 35), together with their associated confidence intervals. At first glance, we observe that the location patterns of these sectors differ considerably from the first analysis. In fact, as is well known, this type of analysis is sensitive to the benchmark being considered. Two aspects related to the confidence intervals also stand out. First, they are not as narrow as in the first case and, second, the smaller the sector is, the wider the confidence interval will be.

[20] These sectors are 17, 18, 22, 24, 28, 31, 32, 33 and 37.

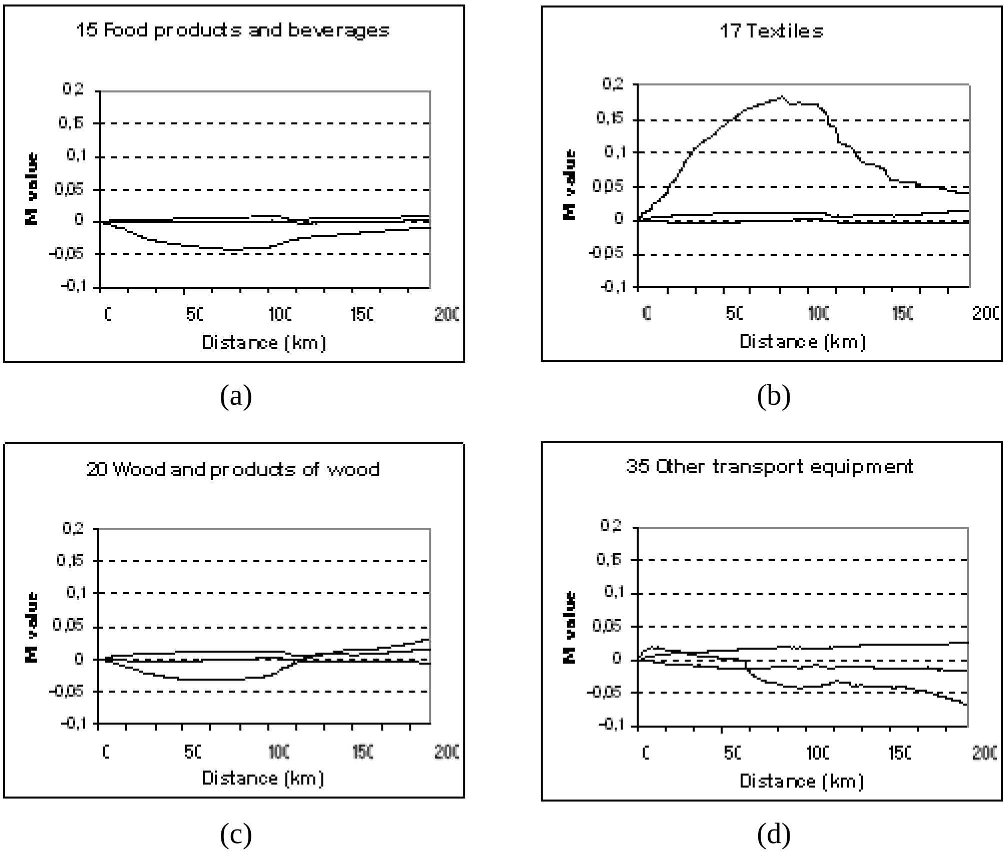


Figure 7. Spatial location patterns (M_{TM}).

We are going to use sector 35, *Other transport equipment*, to exemplify the results coming from the two benchmarks. This will enable us to compare the resulting location patterns.

In Figure 5d, we can see the spatial distribution of firms from sector 35, in the Spanish territory. It can be seen that the establishments in this sector are distributed in small clusters around Madrid, Barcelona, Vigo and the Basque Country, as well as along coastal areas in general.

If we compare the outcomes obtained using both benchmarks (Figures 6d and 7d), it becomes clear that the resulting location patterns are very different. In fact, the location pattern shown in Figure 7d has characteristic features that are more consistent with the real distribution of firms (shown in Figure 5d) than Figure 6d. The apparent concentration of sector 35 that appears in Figure 6d is partly due to an inappropriate benchmark. Indeed, when the M_{CSR} function is used, sector 35 presents significant concentration up to a radius length of 186 km. However, when we control for the 'first nature' factors and for the general tendency of economic activity to agglomerate, using the M_{TM} function, we achieve results that are more realistic. In this case significant concentration is observed up to a radius of 28 km and the maximum significant peak is reached at a distance of 9 km. Furthermore, significant dispersion is found from kilometre 66 onwards. Thus, we note that the results obtained from the M_{TM} function describe the real distribution of establishments in space in a more accurate way.

The rest of the sectors analysed using the second benchmark, presented in Table 2, also show different location patterns. A clear example of this fact is that not every sector presents concentration compared to manufacturing firms as a whole, whatever the length of the radius considered, as happens with the CSR benchmark. Nevertheless, as was to be expected, we found a coincidence. The highest concentrated sectors, i.e. those that reach the highest M value, are the same as the ones in the first analysis and in the same order: 19, 17, 32, 33, 22, 24 and 31. Obviously, the M_{TM} value of these sectors is not as high as the M_{CSR} value, because in this case we compare each sector with the location of overall manufacturing and not with complete spatial randomness.

It may be interesting to compare the above-mentioned results with those obtained by Duranton and Overman (2005) in the UK. Surprisingly, they are very similar. On the one hand, they find that the localized sectors in the UK are 17, 18, 19, 22, 30, 31 32 and 33, which almost coincide with the most concentrated sectors in Spain. On the other hand, the least concentrated sectors in Spain match those non-localized sectors in the UK perfectly, i.e. 15, 20 and 26. Therefore, it can be observed that manufacturing sectors tend to follow similar patterns of location between countries, at least this seems to be the case between Spain and the UK. Additionally, the most concentrated sectors in France and the USA are

Textile (17) and Leather products (19),[21] these results also coinciding with the most concentrated sectors in Spain and the UK.

Alonso-Villar et al. (2004) also studied the geographical concentration of Spanish industry, between 1993 and 1999,[22] and concluded that the most highly concentrated industries, according to the Maurel and Sédillot index, are 19, 17, 32, 22, 33 and 24. As we can see, these results are the same as ours. Hence, thanks to the results obtained by these authors, we can also deduce that, broadly speaking, the spatial location patterns of Spanish manufacturing sectors have not varied significantly in recent years, since the highest concentrated sectors are still the same as in 1999, thus showing some temporal persistence.

INSERT TABLE 2 ABOUT HERE

In spite of this regularity, every Spanish manufacturing sector possesses its own singularities and its patterns of location differ meaningfully from one to another. In fact, the *persistence* or spatial dimension of the cluster varies depending on the sector considered. Hence, we classify all of the sectors analysed into five groups. First, type 0 sectors are those formed by industries that do not present statistically significant concentration or dispersion in comparison to the total manufacturing industry. Second, type 1 sectors include industries that show a greater tendency to concentrate than the manufacturing as a whole at all distances under consideration. Type 2 sectors consist of those industries that are systematically less concentrated than the overall manufacturing industry, that is, they show just relative dispersion patterns. Type 3 industries are relatively concentrated at low distances and dispersed at large distances. Finally, type 4 sectors include those industries that are relatively dispersed at low distances, while at long distances they are more concentrated than manufacturing as a whole.

[21] See Maurel and Sédillot (1999) and Ellison and Glaeser (1997).
[22] Nevertheless, they only presented results for 1999, since not many differences were observed throughout the whole period.

The classification of the different sectors appears in the last column of Table 2, 'Type of sector'. On the one hand, it can be seen that 10 sectors (17, 19, 21, 22, 24, 25, 31, 32, 33 and 34), half of the total number that were considered, present a stronger tendency to cluster than manufacturing firms as a whole at all distances (Type 1), whereas just one sector presents only dispersion in relation to the manufacturing industry as a whole at all distances (Type 2). Finally, it should be noted that only sectors 18 and 37 do not present significant divergence in their tendency to cluster with regard to manufacturing sectors as a whole (Type 0).

On the other hand, we can see that the rest of the sectors present different location patterns depending on the spatial scale chosen, that is to say, depending on the length of the radius being considered. Hence, sectors 27, 28, 29 and 35 show concentration patterns, as compared to manufacturing as a whole, at low distances and relative dispersion at large distances, that is to say, concentration takes place on a relatively small scale (Type 3). Consequently, we may deduce that the establishments in these sectors are distributed in small clusters, presenting dispersion when the distances become longer. Finally, sectors 20, 26 and 36 are relatively dispersed at low distances and more concentrated than manufacturing as a whole at long distances (Type 4). In the case of sectors 20 and 26, however, this tendency to cluster in relation to overall manufacturing at long distances is quite weak and, in the three cases, the distance at which this tendency appears is very long. As we can see in Table 2, we only find relatively significant concentration patterns in these sectors from 137, 145 and 106 km onwards, respectively, and so these three sectors can be considered to be relatively dispersed.

Taking into account the M_{TM} value from the fourth column in Table 2, we can deduce that dispersion happens on different scales and the most highly dispersed sectors in Spain are (15) Food products and beverages, (20) Wood and products of wood, and (26) Other non-metallic mineral products. These dispersed sectors, which have an elevated dependence on natural resources, are related to food or to the primary sector. Moreover, these sectors are also likely to be made up of specialised manufacturers that disperse their establishments to supply the different markets in the best possible way.

Alternatively, if we pay attention to the sectors that have been classified as the most highly concentrated, it can be seen that the agglomeration forces that explain this concentration do not exhibit particular characteristics. On the one hand, the two sectors that show a higher level of concentration in Spain, 19 and 17, are clearly low-tech. We presume that the geographical concentration presented by these sectors is wholly due to *historical trends*.[23] On the other hand, *technological spillovers* seem to be the main reason for location in sectors 31, 32 and 33. Finally, sectors 22 and 24 are the ones for which the search for *skilled labour* appears to play a decisive role in their decision to concentrate. This indicates that 'knowledge spillovers' are not the only factors determining the concentration of activity. Indeed, there are also many other factors such as local labour pooling, natural advantages, tradition, transport costs or upward and forward linkages[24] that can be factors determining this concentration and which play an important role in the patterns of localization of each sector.

Hence, although according to the literature high-tech sectors may be the most highly concentrated, this is not so in our analysis. In fact, it does not occur in the UK, France or in the USA either. Thus, Devereux et al. (2004) stressed that '*the most geographically concentrated industries appear to be relatively low-tech*' and Maurel and Sédillot (1999) found that the most concentrated sectors in France are textile and leather products, two of the most traditional and low-tech sectors. Similar results can also be found for the United States. Thus, in Chapter 2 of Krugman (1991a) it is said that the sectors with a higher degree of concentration are not high-tech, but rather they are sectors related to the textile industry. Nevertheless, we are not trying to say that the high-tech sectors are not concentrated, we just want to draw attention to the fact that low-tech sectors can

[23] They have probably settled and clustered in the same area since the Industrial Revolution.
[24] Emphasised in this way by Krugman (1991a).

also be concentrated. As a result, the diversity of forces that, according to the theory, can cause agglomeration seems to be present with different degrees of intensity in each sector.

With regard to the weight of sectors that show concentration or dispersion, it can be observed that quite a lot of sectors show concentration patterns (14 out of 20). The percentages of manufacturing firms and workers employed in these concentrated sectors are 65% and 67% respectively, whereas 35% of the manufacturing firms and 33% of manufacturing workers belong to dispersed sectors. Therefore, we can state that a larger proportion of manufacturing employees work in sectors with concentration patterns and that these sectors have a larger proportion of firms.

Finally, the agglomerative strengths belonging to each sector, which pull economic activities together, may weaken at long distances and determine the differences in the size of the clusters and in their spatial sequence. The specific location of firms is the result of the trade-off between centripetal (external economies, scale economies, technological spillovers, specialised factor markets, and so one) and centrifugal forces (diseconomies of agglomeration, immobile factors, land rents, etc.) and this is what will determine the differences in the size of each cluster. At first, the increase in firms located in an area creates a self-reinforcing process of agglomeration, which leads to a progressive increase in the centripetal forces associated with this location. Given the intensity of centripetal forces, an increase in the radius (r) and the corresponding increase in distance may reduce the incentive to locate in a particular cluster. Thus, this trade-off between the centripetal and the centrifugal forces does not necessarily increase or decrease monotonically with distance. For this reason, it is interesting not only to analyse the average values of the M function at each radius, but also its variations when we change the radius, that is, $\Delta M/\Delta r$ (the marginal M_{TM} value at each distance). This marginal M_{TM} value informs us about the increase in the number of neighbours in each sector when *r* becomes higher as compared to the increase in neighbours of the overall manufacturing industry.

In Appendix 2, we can see this information for every sector that was considered; nevertheless, we are going to give a detailed description of the location patterns of four sectors, which present a higher level of concentration. Thus, in Figure 8, we can see the M_{TM} value (continuous line) and the marginal M_{TM} value (dashed line) for sectors 17 (textiles), 19 (tanning and dressing of leather), 24 (chemical and chemical products) and 32 (radio, televisions and other appliances). On observing these graphics, some questions come to mind: *What is the distance at which the greatest increases in the relative density of neighbours are produced? Do these increases present any kind of regularity?*

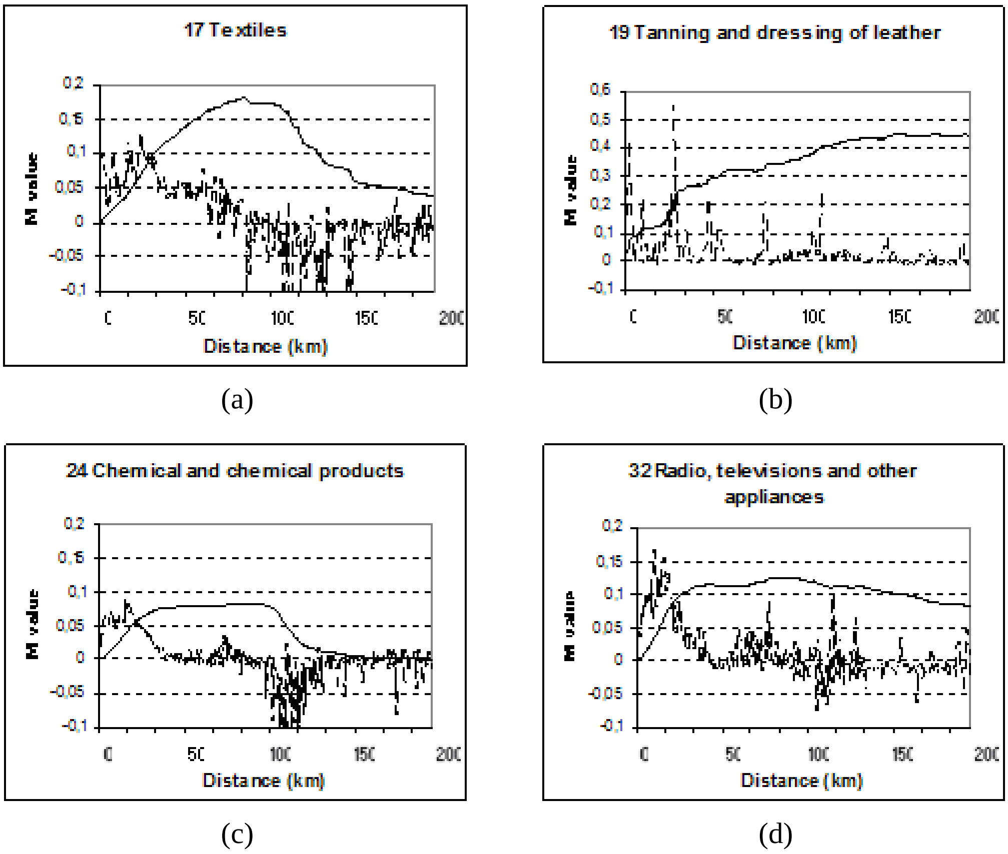


Figure 8. Spatial location patterns (M_{TM} and marginal M_{TM} value).

The distances at which we can find the maximum increase in neighbours (maximum $\Delta M/\Delta r$) vary considerably for each sector, depending on the agglomerative strengths that are specific to each sector. These distances will be called '*distance of maximum increase'* and are summarised in Table 3. In this table, we can compare the distances at which an absolute maximum in M_{TM} is found (absolute M_{TM}) with the distances at which maximum increases in M_{TM} take place (marginal M_{TM}). It can also be observed how the two values complement each other in order to give us more detailed information about the location patterns of each sector.

INSERT TABLE 3 ABOUT HERE

In sector 17, we can see that the marginal M_{TM} value presents four noticeable peaks at the distances of 2, 8, 17 and 25 km. These increases in the number of neighbours at short distances can be interpreted as the existence of nearby clusters (or micro-clusters) in the textile industry. Moreover, we find new peaks when we increase the distance and the radius measures 62, 69 and 73 km, respectively. This can be due to the existence of new clusters, which are separated from the previous ones, in other regions. Sector 19 also shows multiple nearby clusters up to a similar distance (27 km). In fact, we find significant increases in the number of neighbours when r measures 2, 9, 24, 26 and 27 km. Thus, sectors 17 and 19 allow us to observe similar location patterns at short distances, and the distances at which the clusters appear almost coincide with one another. However, as you can see in *Appendix 2*, the increase in neighbours in the textile sector is more regular than in sector 19, since two great increases in the number of neighbours appear in the latter at distances of 2 and 27 km.

The centripetal forces of the previously analysed sectors, 17 and 19, may be different from those of sectors 24 and 32, since the initial spatial scale at which multiple nearby clusters appear in these sectors is smaller (16 and 18 km, respectively, instead of 25 and 27 km). Indeed, sectors 17 and 19 are traditional, low-tech sectors whereas 24 and 32 are high-tech sectors. Therefore, we can assume that the technological spillovers may reduce the distance at which the clusters are produced. Thus, the nature of the centripetal and centrifugal forces of each sector will determine the differences in the size of the clusters and the sequence in which clusters appear within the territory.

5. Conclusions

This paper analyses the spatial location patterns of manufacturing firms in Spain. To do this, we use a distance-based method, which allows us to consider space as continuous and avoids the drawbacks of the administrative scale, and thus geographic concentration can be measured at different scales. Therefore, this method enables us to know the intensity of concentration or dispersion of each Spanish manufacturing sector, the distance at which its maximum level is obtained, and the spatial sequence of the increases in the said intensity. Moreover, we can detect whether the departures from randomness are statistically significant.

The characteristics of the location patterns of the Spanish manufacturing sectors can be attributed, in our first analysis, to various forces acting simultaneously. Thus, the location of the activity may be due, first of all, to the dissimilarities in such natural features as mountains, rivers or harbours, that is, 'first nature'. Secondly, it may be due to the general tendency of manufacturing firms to agglomerate and, thirdly, to the idiosyncratic tendency of each particular sector to concentrate. In fact, by using '*complete spatial randomness*' as the benchmark we find that every sector presents a general tendency to concentrate, whatever the distance considered. Furthermore, we find a strong regularity in the distance at which the highest concentration is reached (85-91 km) that may also be due to the benchmark employed. Moreover, the most highly concentrated sectors are both traditional (predominated by textile-related industries) and high-tech industries. This also occurs in the UK, France or the USA, as we have already commented, and it coincides with the Spanish results obtained in 1999. From this, we can conclude that these location patterns have not varied significantly in Spain in the last few years and that manufacturing sectors in different countries tend to follow similar patterns of location. These findings lead us to believe that this is more likely to be due to idiosyncratic features of the sectors (technology, input structure, transport costs, and so forth) than to characteristics of the countries themselves.

In our second analysis, we control for the first nature and for the general tendency of manufacturing firms to agglomerate, which allows us to isolate the specificities of each sector and their idiosyncratic tendency to concentrate once they have been controlled for their industrial concentration. Besides, we minimize the drawbacks associated with the use of the rectangular area as area of study. In this way, although the most highly concentrated sectors coincide in both analyses, not every sector presents concentration as compared to the overall manufacturing industry. In fact, our results show that about 70% of Spanish manufacturing sectors and a similar proportion of manufacturing employees are localised. With regard to the specific location patterns of each sector, half of them present a stronger tendency to cluster than the manufacturing industry as a whole, no matter what the distance is; in fact just one sector presents dispersion at every radius measured and the rest present concentration or dispersion depending on the spatial scale that is chosen. Finally, using '*total manufacturing*' as the benchmark, our index is comparable across industries, it controls for the overall agglomeration of manufacturing and for industrial concentration, it is unbiased with respect to scale and aggregation, and it gives an indication of the significance of the results.

By means of the marginal M_{TM} value ($\Delta M/\Delta r$), which informs us about the increase in neighbours when r becomes higher in every sector relative to the increase in neighbours in the overall manufacturing, it can be seen that the distances at which we can find the maximum increase in neighbouring firms vary considerably among sectors. In all probability, the differences in the size of the clusters and the sequence in which clusters appear in the territory are determined by the nature of the centripetal and centrifugal forces of each sector. As a result, we find multiple nearby clusters in the most highly concentrated sectors, but the initial spatial scale at which we find these multiple micro-clusters is smaller in high-tech sectors (i.e. 16 km) than in traditional, low-tech sectors, where it is 25 km. This may be because the centripetal forces are stronger in high-tech sectors. Finally, when the spatial scale considered becomes larger, new clusters appear and this indicates the existence of new agglomerations of firms in different regions.

Finally, we should just add that we are aware of the aggregation of data in our analysis, given that we are dealing with sectors that are aggregated at the two-digit level. This aspect may generate a clear compensation effect between the different branches of each sector, since the most aggregated and the most dispersed ones can compensate each other. Consequently, the next step in our analysis could be to try to find out whether the location patterns presented by the different branches of each sector are similar to or different from those displayed by the sector itself.

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Table 1. Location patterns of Spanish manufacturing sectors (M_{CSR})

Sectors (NACE 93 - Rev. 1)	Significant concentration	Significant dispersion	Significant peak		Type of cluster
			M_{CSR} value	Distance (r)	
15 Food products and beverages	All distances	---	0,05	100 km	2
17 Textiles	All distances	---	0,27	87 km	1
18 Wearing apparel and dressing	All distances	---	0,09	87 km	2
19 Tanning and dressing of leather	All distances	---	0,50	156 km	2
20 Wood and products of wood	All distances	---	0,08	200 km	2
21 Pulp, paper and paper products	All distances	---	0,16	99 km	1
22 Publishing, printing & recorded media	All distances	---	0,20	85 km	1
24 Chemical and chemical products	All distances	---	0,17	90 km	1
25 Rubber and plastic products	All distances	---	0,13	97 km	1
26 Other non-metallic mineral products	All distances	---	0,08	200 km	2
27 Basic metals	All distances	---	0,10	80 km	1
28 Fabricated metal products	All distances	---	0,09	86 km	1
29 Other machinery and equipment	All distances	---	0,13	96 km	1
31 Electrical machinery	All distances	---	0,16	90 km	1
32 Radio, televisions & other appliances	All distances	---	0,21	91 km	1
33 Instruments	All distances	---	0,21	90 km	1
34 Motor vehicles and trailers	All distances	---	0,11	100 km	1
35 Other transport equipment	0-186 km	189-200 km	0,07	64 km	1
36 Furniture and other products	All distances	---	0,12	183 km	2
37 Recycling	All distances	---	0,09	86 km	1

Table 2. Location patterns of Spanish manufacturing sectors (M_{TM})

Sectors (NACE 93 - Rev. 1)	Significant concentration	Significant dispersion	Significant peak		Type of cluster
			M_{TM} value	Distance (r)	
15 Food products and beverages	---	All distances	-0,04	80 km	2
17 Textiles	All distances	---	0,18	87 km	1
18 Wearing apparel and dressing	---	---	---	---	0
19 Tanning and dressing of leather	All distances	---	0,45	157 km	1
20 Wood and products of wood	137-200 km	0-120 km	-0,03	64 km	4
21 Pulp, paper and paper products	All distances	---	0,07	103 km	1
22 Publishing, printing & recorded media	All distances	---	0,12	36 km	1
24 Chemical and chemical products	0-147 km	---	0,08	83 km	1
25 Rubber and plastic products	0-167 km	---	0,04	90 km	1
26 Other non-metallic mineral products	145-200 km	0-123 km	-0,03	60 km	4
27 Basic metals	42-84 km	127-200 km	0,02	63 km	3
28 Fabricated metal products	34-87 km	97-200 km	0,01	66 km	3
29 Other machinery and equipment	0-121 km	130-200 km	0,04	77 km	3
31 Electrical machinery	0-131 km	---	0,08	81 km	1
32 Radio, televisions & other appliances	All distances	---	0,13	83 km	1
33 Instruments	0-175 km	---	0,12	81 km	1
34 Motor vehicles and trailers	51-100 km	---	0,02	80 km	1
35 Other transport equipment	0-28 km	66-200 km	0,02	9 km	3
36 Furniture and other products	106-200 km	25-93 km	0,06	193 km	4
37 Recycling	---	---	---	---	0

Table 3. Distance of maximum intensity of neighbouring firms

Sectors (NACE 93 - Rev. 1)	Absolute M_{TM}	Marginal M_{TM} [(a)]
15 Food products and beverages	80 km	
17 Textiles	87 km	2/8/17/25 km
18 Wearing apparel and dressing	---	
19 Tanning and dressing of leather	157 km	2/9/24/26/27 km 48/81/113 km
20 Wood and products of wood	64 km	
21 Pulp, paper and paper products	103 km	17 km
22 Publishing, printing & recorded media	36 km	2-6/17 km
24 Chemical and chemical products	83 km	4-6/13/16 km
25 Rubber and plastic products	90 km	18 km
26 Other non-metallic mineral products	60 km	
27 Basic metals	63 km	
28 Fabricated metal products	66 km	
29 Other machinery and equipment	77 km	11 km
31 Electrical machinery	81 km	10 km
32 Radio, televisions & other appliances	83 km	5/7/ 9-10 km 12/16/18 km
33 Instruments	81 km	4/8-10/14/17 km
34 Motor vehicles and trailers	80 km	
35 Other transport equipment	9 km	2 km
36 Furniture and other products	193 km	
37 Recycling	---	

[(a)] Those sectors in which the 'marginal M_{TM} value' does not appear is because it does not add relevant information.

Appendix 1

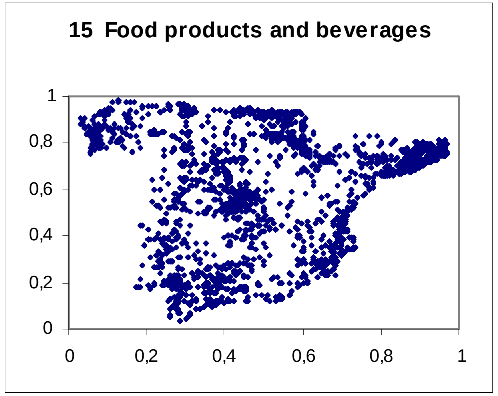
Table A1. Additional descriptive information about Spanish manufacturing sectors

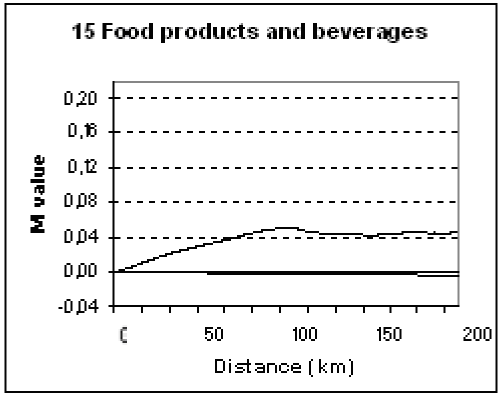
Sectors (NACE 93 - Rev. 1)	Number of firms	Number of employees	Technological intensity[25]
15 Food products and beverages	5761	356314	L
16 Tobacco products	6	1226	L
17 Textiles	1949	81818	L
18 Wearing apparel and dressing	1710	59286	L
19 Tanning and dressing of leather	1698	46708	L
20 Wood and products of wood	2340	75844	L
21 Pulp, paper and paper products	837	56890	L
22 Publishing, printing & recorded media	3004	130222	L
23 Coke, refined petroleum products	12	16417	M-L
24 Chemical and chemical products	1722	158238	H
25 Rubber and plastic products	2165	138488	M-L
26 Other non-metallic mineral products	3413	225792	M-L
27 Basic metals	986	137066	M-L
28 Fabricated metal products	8094	267568	M-L
29 Other machinery and equipment	3015	161407	M-H
30 Office machinery and computers	77	6374	H
31 Electrical machinery	1099	79357	M-H
32 Radio, televisions & other appliances	344	31593	H
33 Instruments	376	19528	H
34 Motor vehicles and trailers	876	192873	M-H
35 Other transport equipment	451	58274	M-H
36 Furniture and other products	2924	100084	L
37 Recycling	228	8095	L

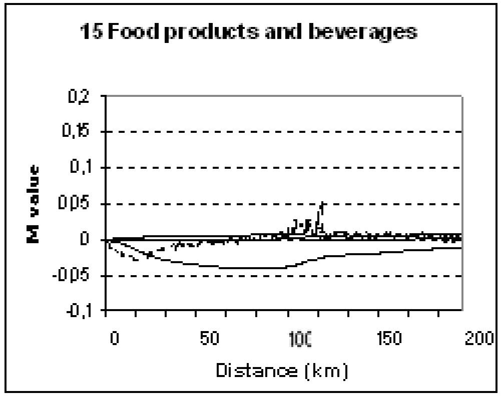
[25] This classification of sectors according to the technological intensity belongs to the National Statistics Institute, meaning H = high, M-H = medium high, M-L = medium low and L = low.

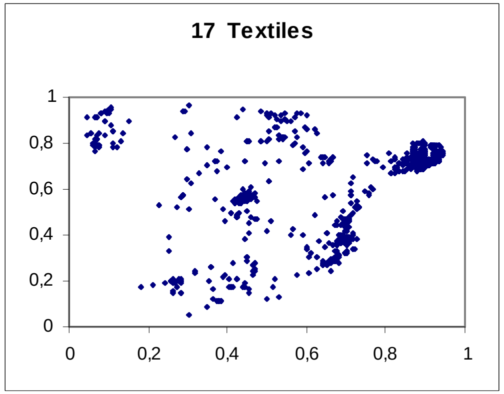
Appendix 2

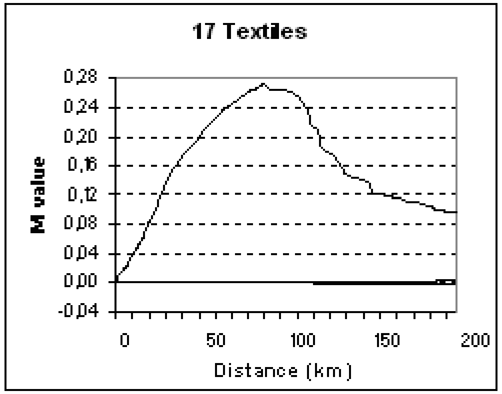
On the one hand, the graphs situated on the left illustrate the spatial distribution of firms from each Spanish manufacturing sector. On the other hand, the graphs in the middle show the spatial location patterns of these sectors measured by the M_{CSR} function, while those on the right show the spatial location patterns measured by means of the M_{TM} function (continuous line), with the addition of the marginal M_{TM} value (dashed line). These two graphs allow us to detect differences between geographical concentration scales according to the sector under consideration.

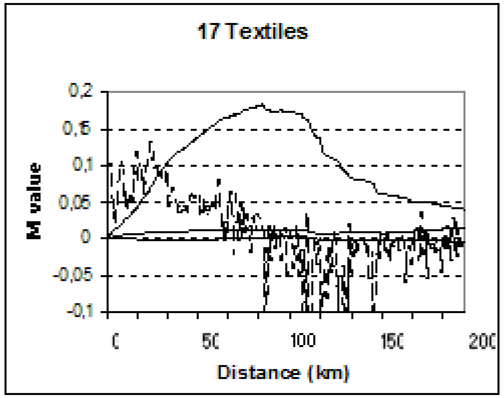

15 Food products and beverages
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

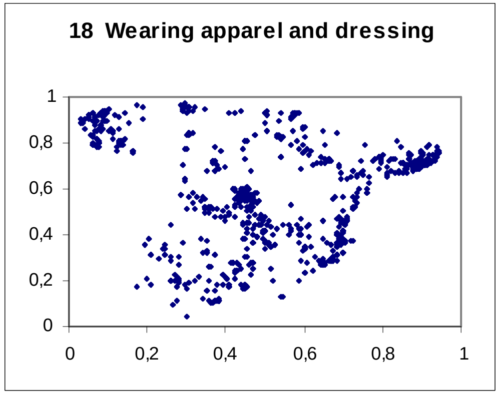

15 Food products and beverages
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

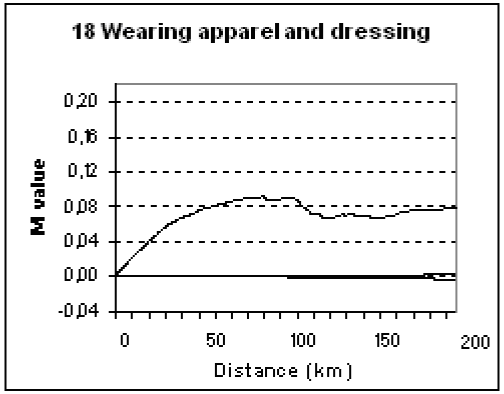

15 Food products and beverages
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

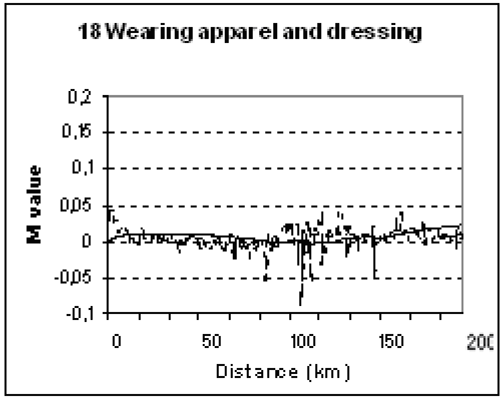

17 Textiles
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

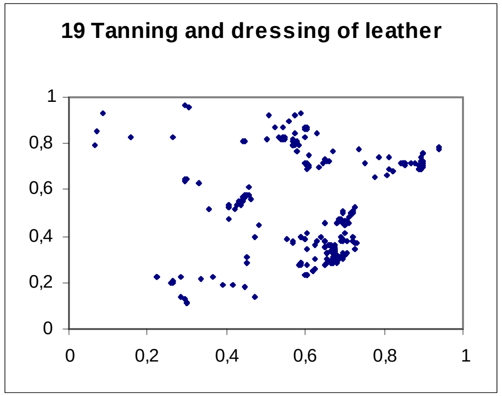

17 Textiles
M value
0,28
0,24
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

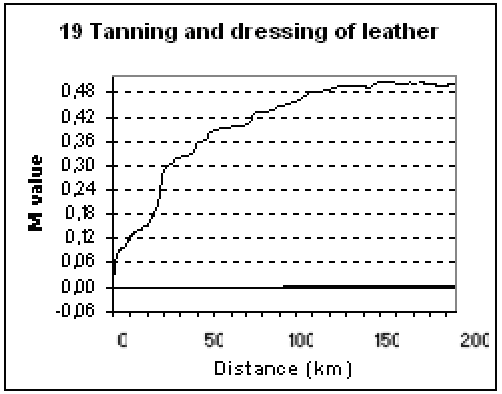

17 Textiles
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

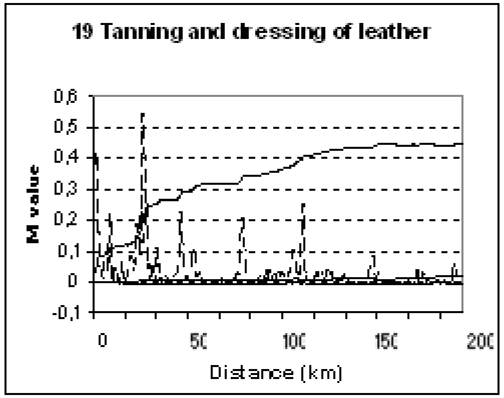

18 Wearing apparel and dressing
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

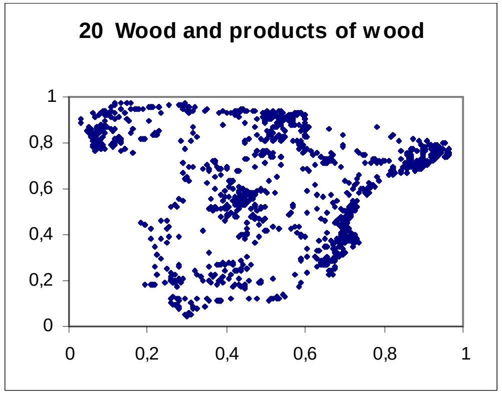

18 Wearing apparel and dressing
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

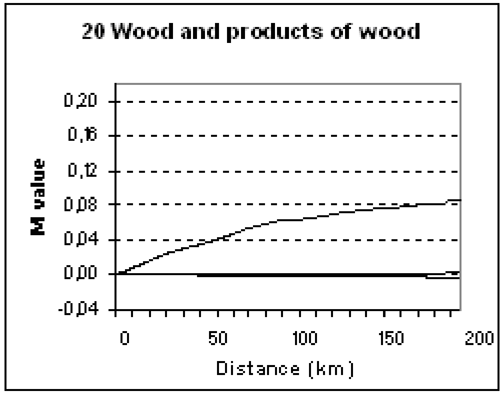

18 Wearing apparel and dressing
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

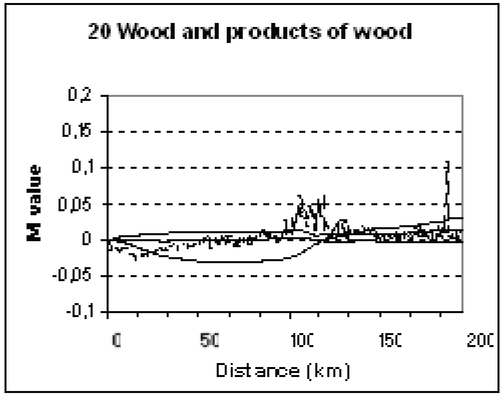

19 Tanning and dressing of leather
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

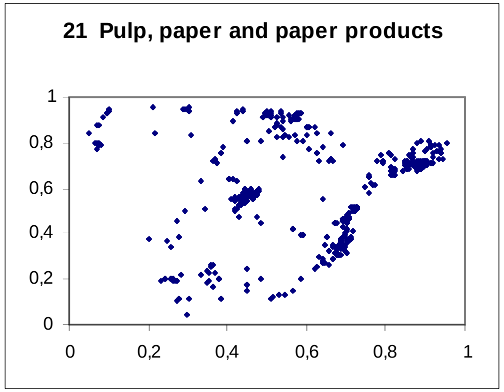

19 Tanning and dressing of leather
M value
0,48
0,42
0,36
0,30
0,24
0,18
0,12
0,06
0,00
-0,06
0
50
100
150
200
Distance (km)

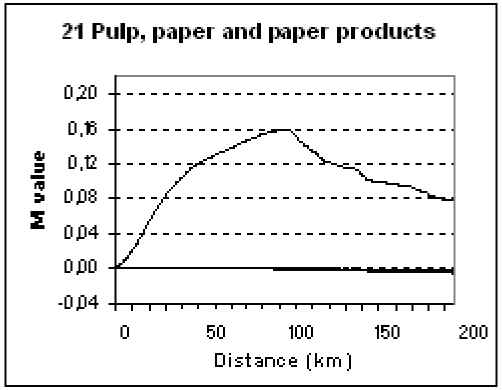

19 Tanning and dressing of leather
M value
0,6
0,5
0,4
0,3
0,2
0,1
0
-0,1
0
50
100
150
200
Distance (km)

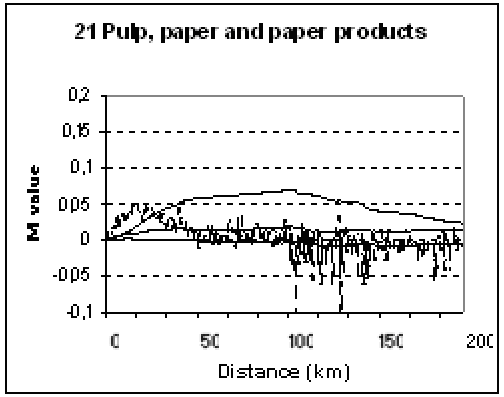

20 Wood and products of wood
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

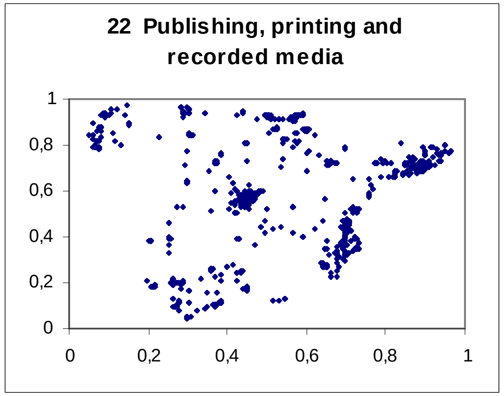

20 Wood and products of wood
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

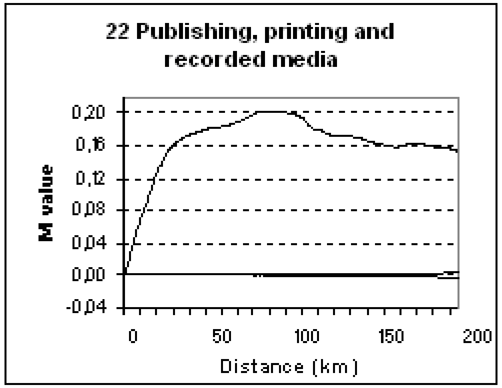

20 Wood and products of wood
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

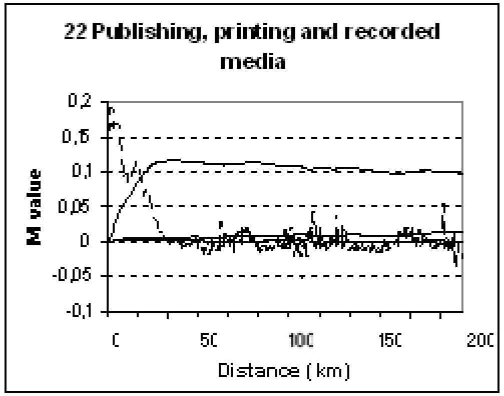

21 Pulp, paper and paper products
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

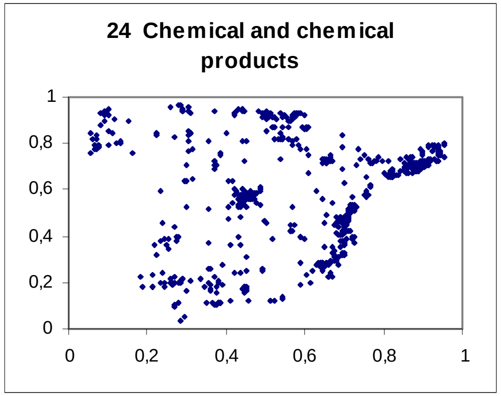

21 Pulp, paper and paper products
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

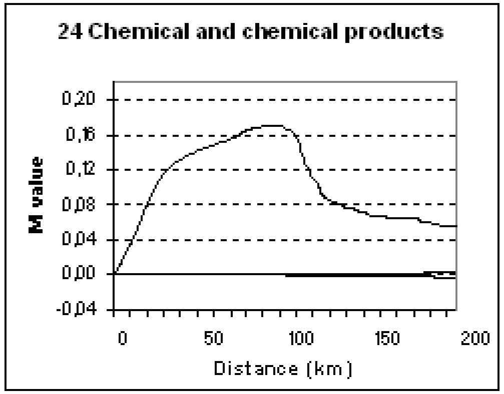

21 Pulp, paper and paper products
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

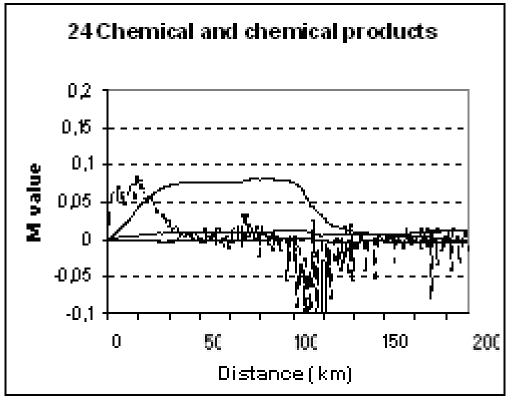

22 Publishing, printing and recorded media
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

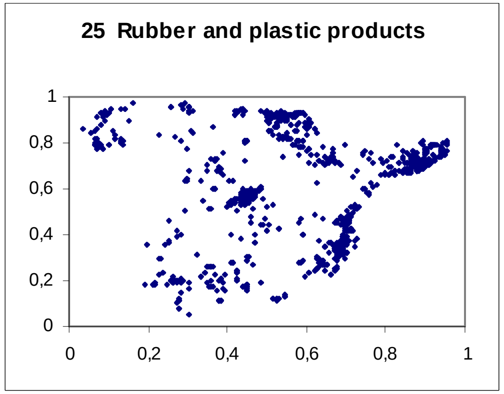

22 Publishing, printing and recorded media
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

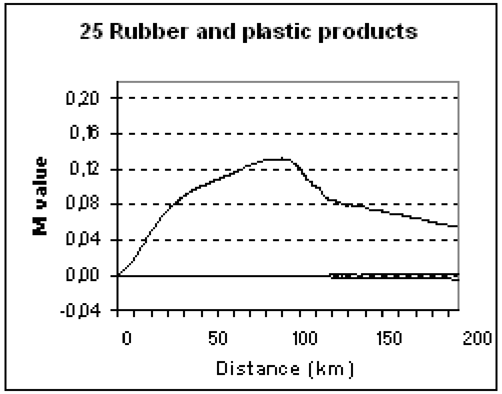

22 Publishing, printing and recorded media
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
50
100
150
Distance (km)

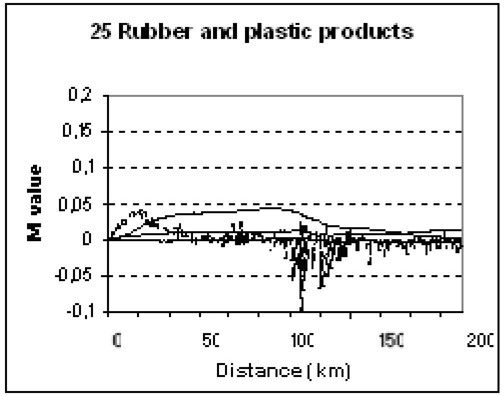

24 Chemical and chemical products
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

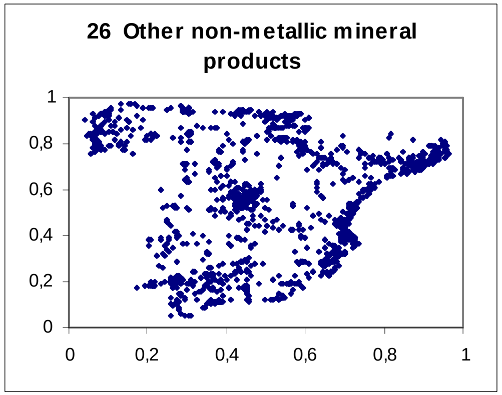

24 Chemical and chemical products
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

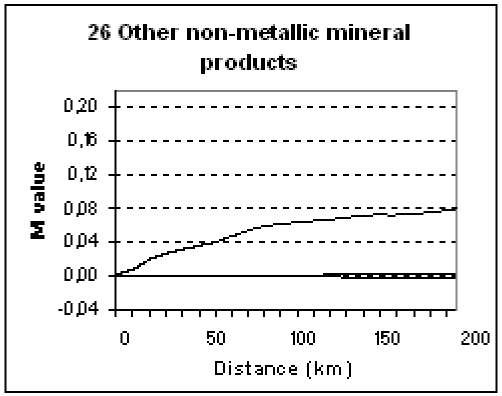

24 Chemical and chemical products
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
150
Distance (km)

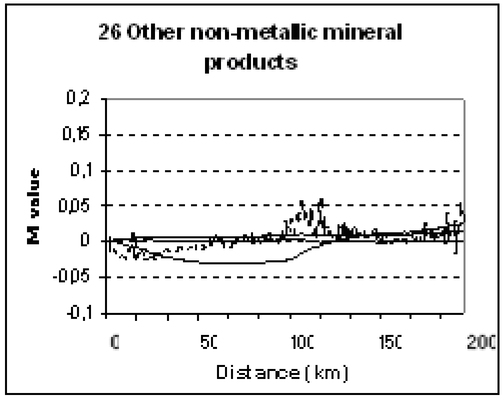

25 Rubber and plastic products

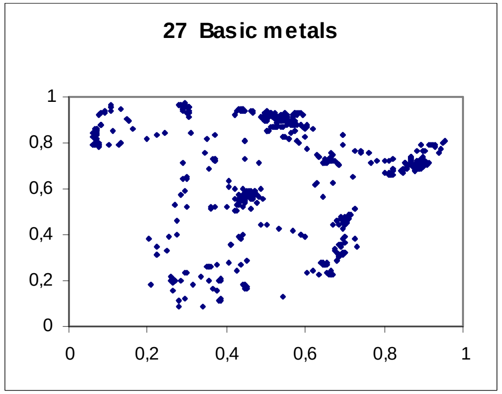

25 Rubber and plastic products
M value
Distance (km)

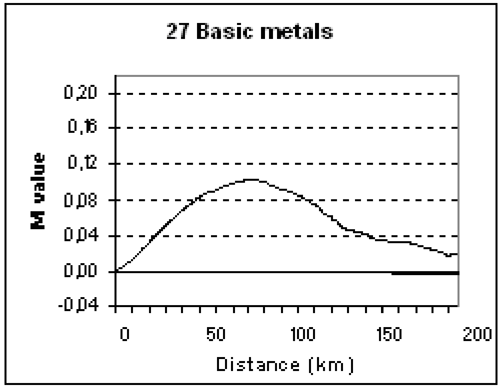

25 Rubber and plastic products
M value
Distance (km)

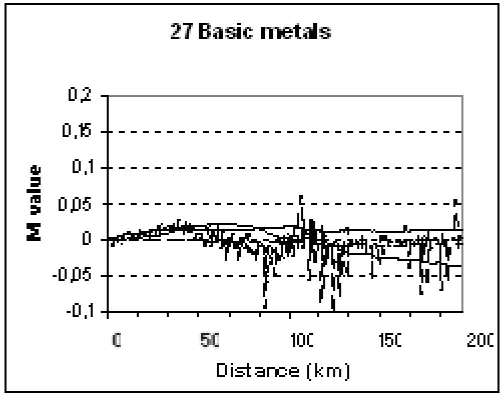

26 Other non-metallic mineral products

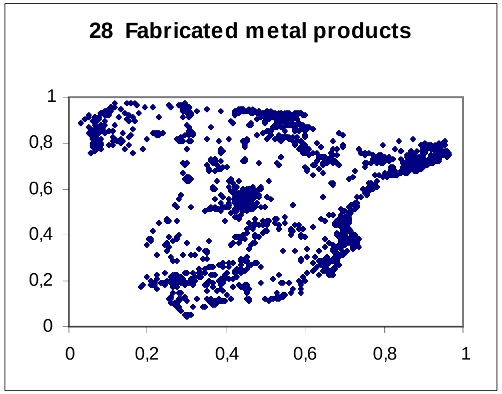

26 Other non-metallic mineral products
M value
Distance (km)

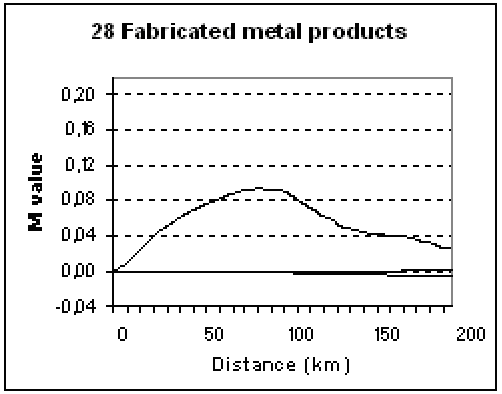

26 Other non-metallic mineral products
M value
Distance (km)

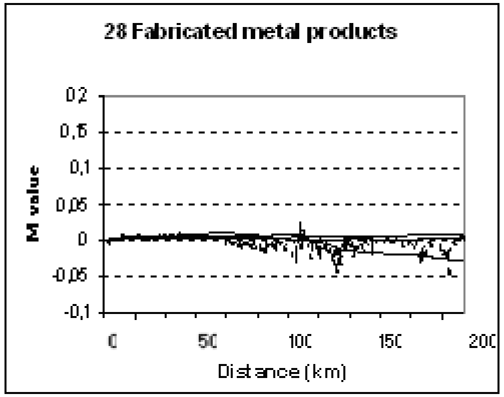

27 Basic metals
0
0,2
0,4
0,6
0,8
1

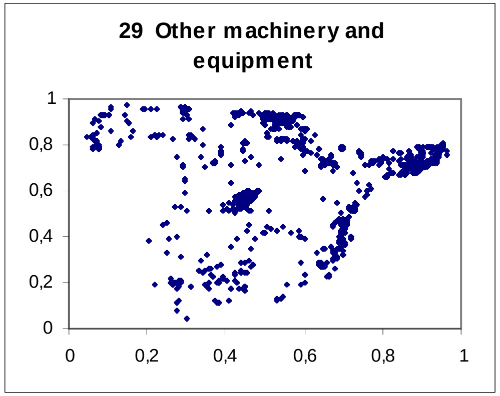

27 Basic metals
M value
Distance (km)

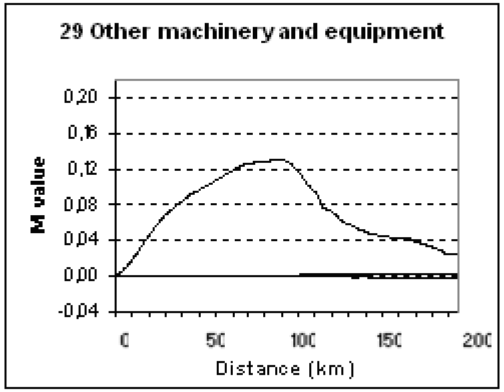

27 Basic metals
M value
Distance (km)

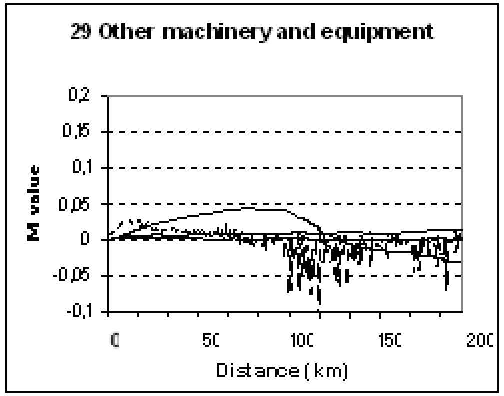

28 Fabricated metal products
0
0,2
0,4
0,6
0,8
1

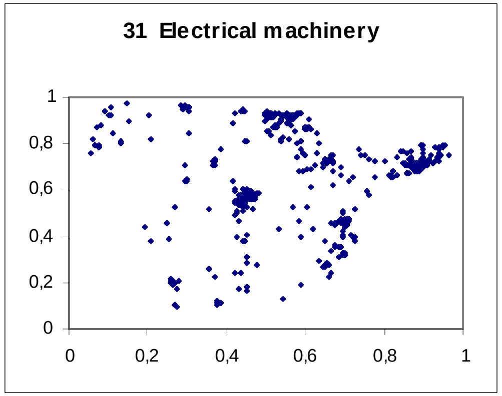

28 Fabricated metal products
M value
Distance (km)

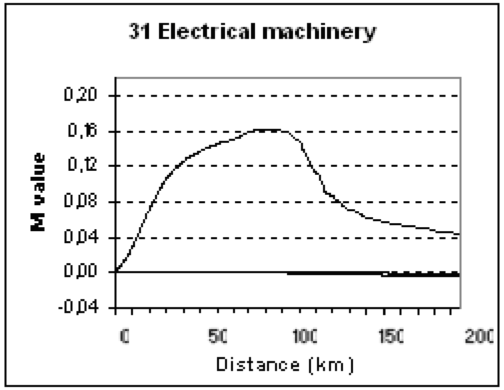

28 Fabricated metal products
M value
Distance (km)

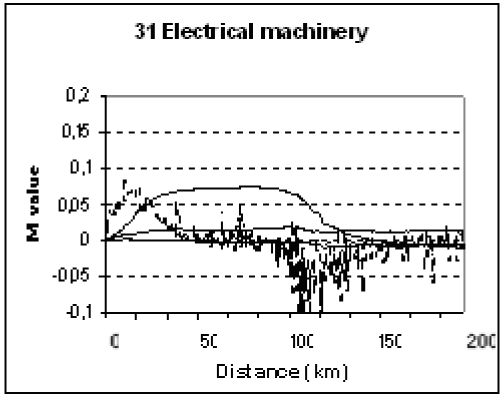

29 Other machinery and equipment
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

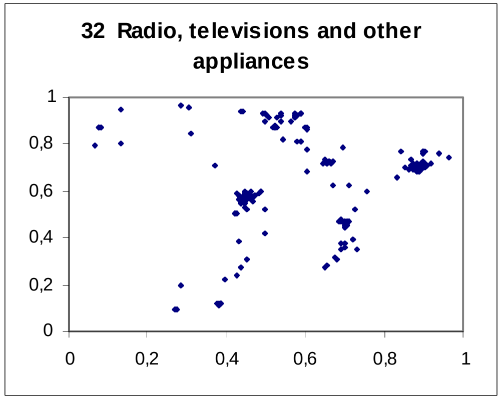

29 Other machinery and equipment
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

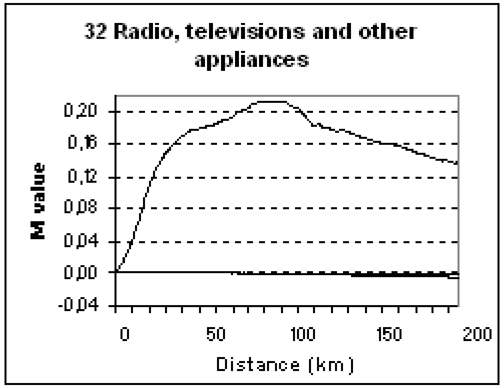

29 Other machinery and equipment
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

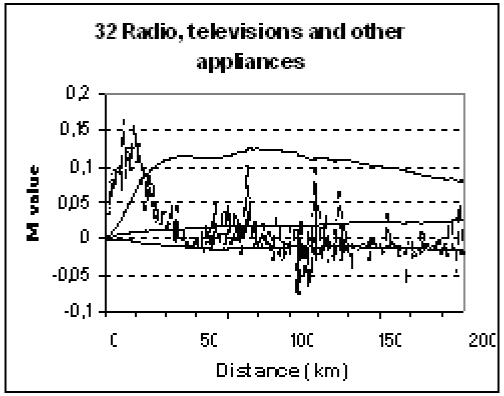

31 Electrical machinery
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

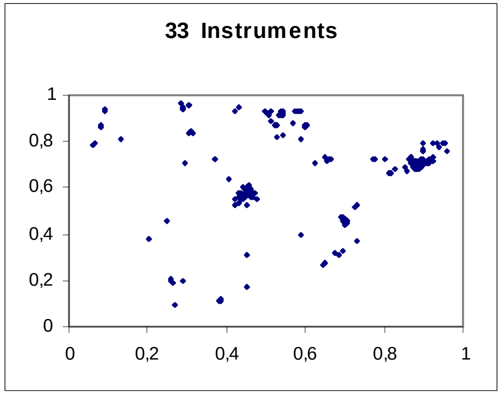

31 Electrical machinery
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

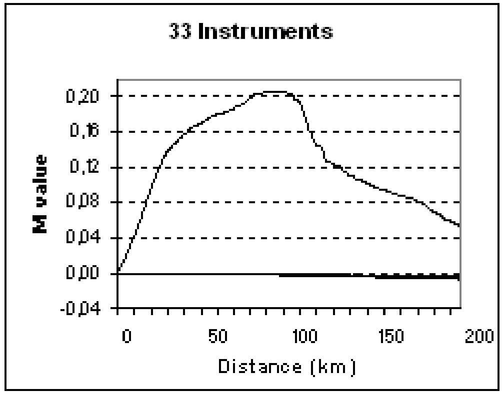

31 Electrical machinery
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

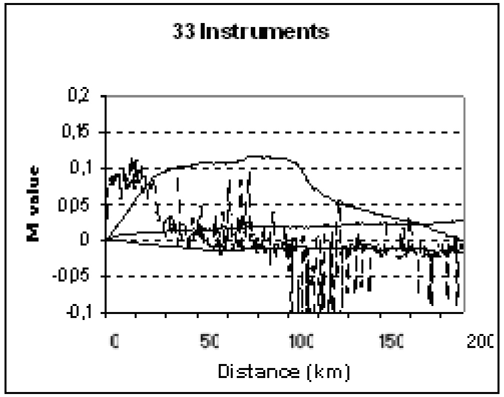

32 Radio, televisions and other appliances
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

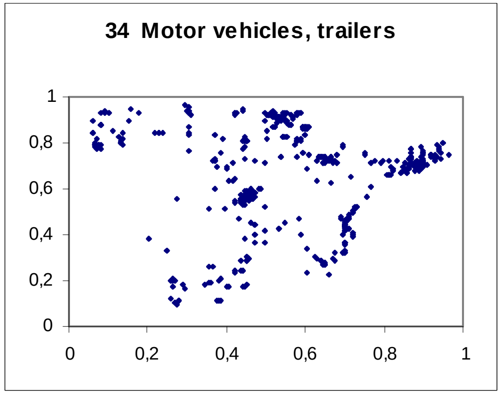

32 Radio, televisions and other appliances
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

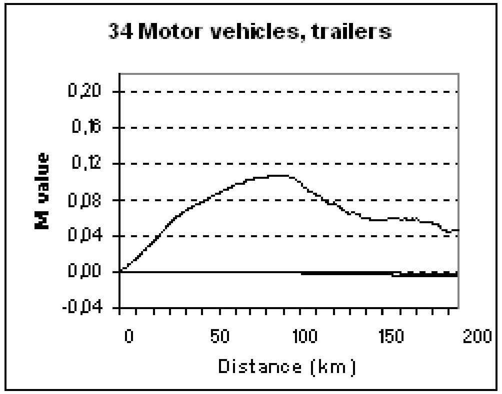

32 Radio, televisions and other appliances
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

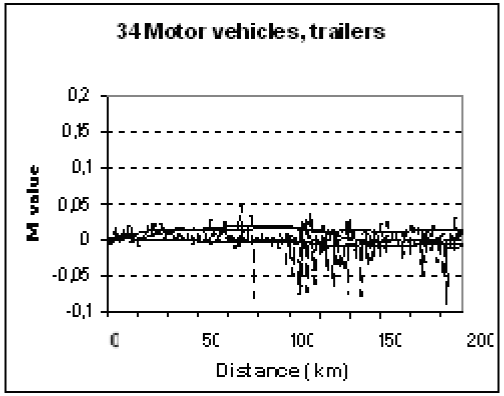

33 Instruments
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

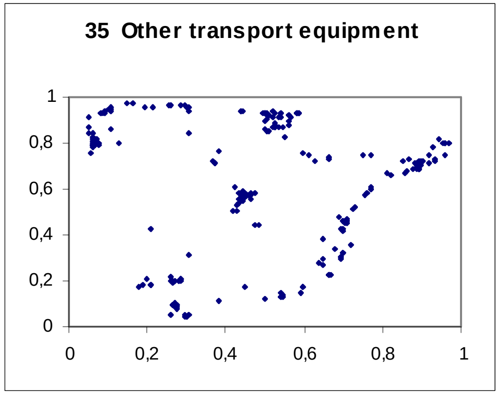

33 Instruments
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

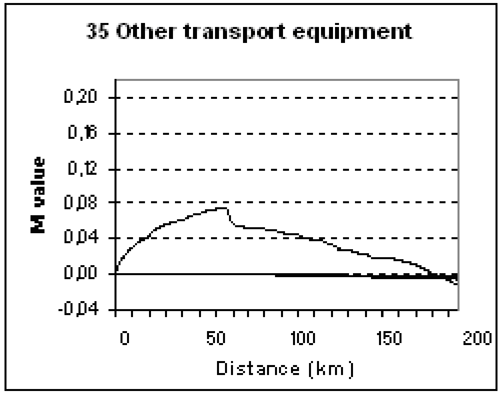

33 Instruments
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)

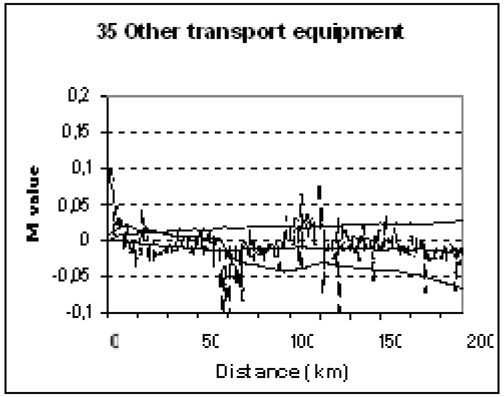

34 Motor vehicles, trailers
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

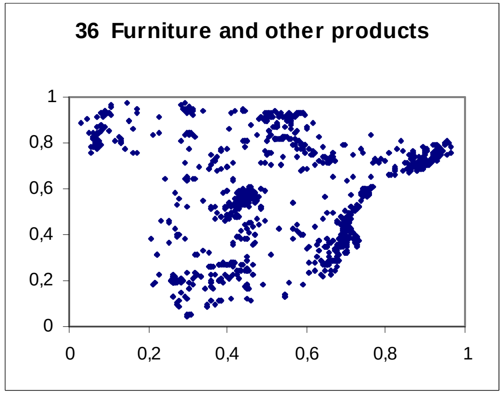

34 Motor vehicles, trailers
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

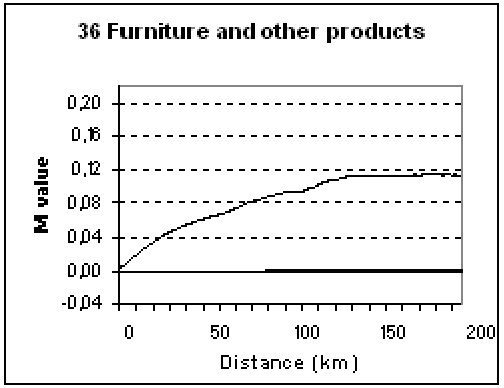

34 Motor vehicles, trailers
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
Distance (km)

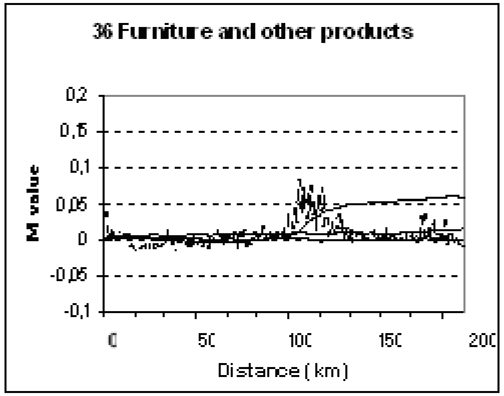

35 Other transport equipment
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1

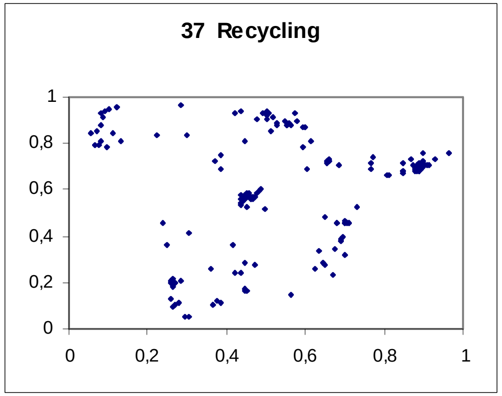

35 Other transport equipment
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)

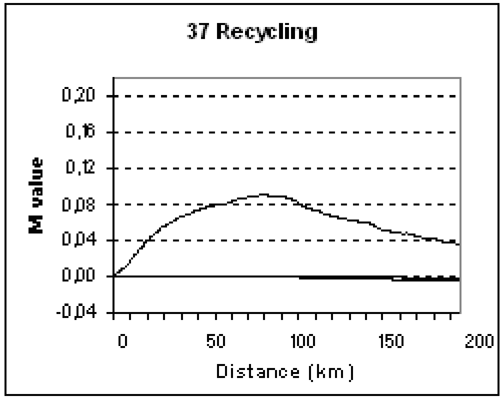

35 Other transport equipment
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
Distance (km)

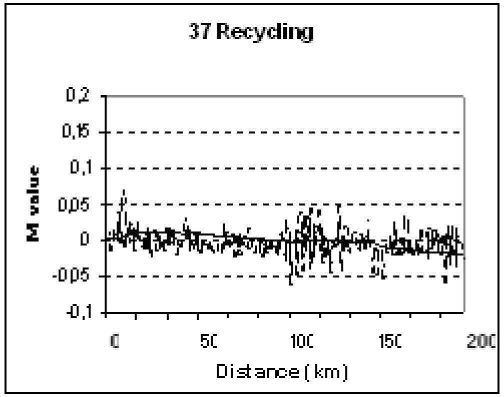

36 Furniture and other products
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1


36 Furniture and other products
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)


36 Furniture and other products
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)


37 Recycling
1
0,8
0,6
0,4
0,2
0
0
0,2
0,4
0,6
0,8
1


37 Recycling
M value
0,20
0,16
0,12
0,08
0,04
0,00
-0,04
0
50
100
150
200
Distance (km)


37 Recycling
M value
0,2
0,15
0,1
0,05
0
-0,05
-0,1
0
50
100
150
200
Distance (km)