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ORIGINAL PAPER

A class of spatial econometric methods in the empirical analysis of clusters of firms in the space

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Abstract In this paper we aim at identifying stylized facts in order to suggest adequate models for the co-agglomeration of industries in space. We describe a class of spatial statistical methods for the empirical analysis of spatial clusters. The main innovation of the paper consists in considering clustering for bivariate (rather than univariate) distributions. This allows uncovering co-agglomeration and repulsion phenomena between the different sectors. Furthermore we present empirical evidence on the pair-wise intra-sectoral spatial distribution of patents in Italy in 1990s. We identify some distinctive joint patterns of location between different sectors and we propose some possible economic interpretations.

Keywords Agglomeration · Bivariate K-functions · Co-agglomeration · Spatial clusters · Spatial econometrics

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1 Introduction

The dominating feature of economic activities is certainly that of clustering both in space and time. However, even if the application of statistical techniques for modelling clustering in time (business cycles) has been a central concern of applied economists for decades, it is only relatively recently that the research has concentrated on the development of appropriate methods to detect spatial clustering of economic activities both on a discrete space and on a continuous space.

The possibility of modelling the spatial dimension of economic activities is of paramount interest for a number of reasons. First of all the study of spatial concentration of economic activities can shed light on economic theoretic hypotheses concerning the nature of increasing returns and the determinants of agglomeration. These hypotheses are of paramount importance in international trade and in economic growth theories. A second important reason is constituted by the fact that the effects of policy measures to foster economic growth and development are strongly dependent on geographical clustering. Finally spatial clustering, as a synonym of regional inequality, is a central political issue as a proxy of individual inequality and as the basis for cross-country inequality.

After the recent reinterpretation of Marshall's (1890) insights on nineteenth century industrial clustering in space due mainly to Krugman (1991) and Fujita et al. (1999), the empirical analysis on this subject has developed along two distinct lines of research. Along the first of these two lines in the literature we record attempts to examine directly the underlying economic mechanism, using the spatial dimension primarily as a source of data. Under this respect panel data or pure spatial regressions are used, employing observable covariates related to space. Such regressions end up constructing a hypothetical representative unit (a "*site*") and concentrate on the impact of differing covariate values on the performance of that representative unit (see e.g., Ciccone and Hall 1996; Jaffe et al. 1993; Rauch 1993; Henderson 2003).

Here we follow the second line of research which attempts to characterize the entire spatial distribution of economic activities relative to a set of hypotheses (e.g., a certain regularity patterns of industrial concentration). In this second instance interest does not rest on the characteristics of a *representative unit*, but rather on the joint behaviour of the different units distributed across space. Along these lines Duranton and Overman (2005) refer to three generations of measures of spatial concentration. A first generation considered Gini-type measures where space played no rule (e.g., Krugman 1991). A second generation (perhaps initiated by Ellison and Glaeser 1997) introduced measures that take into account space and tend to control for the underlying industrial concentration (Maurel and Sedillot 1999; Devereux et al. 2004). Such measures are based on data observed on a grid of administrative areas thus neglecting the problem of the arbitrariness of the geographical partition used. This problem is known in the statistical literature as the modifiable unit problem (Yule and Kendall 1950) and assumes here the specific facet of the modifiable areal unit problems (or MAUP) discussed at length in Arbia (1989). Arbia (2001) and Duranton and Overman (2005) provide an exhaustive account of the advantages of a third generation of measures that looks at maps of points on a continuous, rather than on a discrete, space: following this approach we can easily compare the results across different scales.

In the present paper we look at the distribution of industries as a map of points in the space and we characterize their geographical distribution through the Lotwick–Silverman (Lotwick and Silverman 1982) extension of the spatial statistical non-parametric tool known as the K-function (Ripley 1977). The use of the K functions in economic analysis was first introduced in the literature by Arbia and Espa (1996) and then exploited by Marcon and Puech (2003a,b), by Quah and Simpson (2003) and by Duranton and Overman (2005) amongst the others. Ioannides and Overman (2004) look also at the properties of points on a continuous space, but using a different approach. Compared to previous contributions the major innovation of the present paper is to consider clustering for bivariate (rather than univariate) distributions, which allows uncovering agglomeration and repulsion phenomena between different sectors. The literature often refers to this subject as to co-agglomeration or co-localization (Devereux et al. 2004; Duranton and Overman 2005). The functionals we propose to characterize a joint pattern of points satisfies the five conditions suggested by Duranton and Overman (2005) for a concentration measure.[1] In particular we introduce the use of the K function to control for the underlying industrial concentration.

The theoretical ground on which such a modelling framework is based is well described in Quah and Simpson (2003) where the authors stressed the importance of being able to specify a model determining a *spatial law of motion* and its evolution through time. Quah–Simpson model assumes that each individual economic agent aims at maximizing his own profit by locating his activity where the average spatial return is higher with a gradual time-adjustment based on a cost function. Equilibrium is then achieved by optimizing the choices of each individual economic agent. The result is a (space–time) partial differential equation that expresses the economic activity in each point in time and space as a density. A good way of approaching the empirical analysis of clusters in space is then represented by a modelling framework that is able to describe how such densities change in space conditionally upon the observed pattern of points.

A field were what Quah and Simpson (2003) define as a *spatial law of motion* is particularly theoretically grounded is the analysis of the spatial diffusion of innovation and of technological spillovers. For this reason the empirical part of this paper is devoted to the analysis of the joint location of innovations.

The studies on knowledge spillovers have received increasing importance in the literature on economic growth. In fact some theories explicitly link the presence of innovations to the growth of cities (Jacobs 1969, 1984; Bairoch 1988) seen as the places where the big concentration of individuals, firms and workers create positive

[1] The five requirements suggested by Duranton and Overman (2005) for a concentration measure are the following: any measure (1) should be comparable across industries; (2) should control for the overall agglomeration of manufacturing; (3) should control for industrial concentration; (4) should be unbiased with respect to scale and aggregation; and, finally (5) should also give an indication of the significance of the results.

externalities which, in turn, foster economic growth. Even if economic theory has produced important advances in this direction (Arrow 1962; Romer 1986; Lucas 1988; Porter 1990) empirical evidence are still largely lacking. In fact a large part of the empirical literature concentrated on measuring the impact of technological spillovers on the innovation performance of regions. In many instances the number of patents and the relative citations have been used as proxies of the flow of knowledge and of the related innovative output (Jaffe and Trajtenberg 1996, 2002; Jaffe et al. 2000). One possible approach is based on the notion of knowledge production function introduced by Griliches (1979) which links regional innovative output with measures of regional innovative inputs like R&D expenses (see e.g., Jaffe 1989; Audretsch and Feldman 1996; Acs et al. 1994). These studies provide significant evidence of the impact of localized R&D inputs on the innovation performance of regions. There is comparatively less empirical evidence on the effects of localized knowledge spillovers (Glaeser 1992; Henderson and Kunkoro 1995; Henderson 2003) and no definite answer is yet available to the question whether knowledge flows are favoured by regional specialization within firms or, vice versa, by industrial diversification.

In this paper we wish to show the importance of the distance-based measures of spatial concentration in tackling this important emerging research area and to provide new statistical tools to study the interaction between spatial concentration, regional growth and knowledge spillovers. The layout of the paper is the following. In Sects. 2 and 3 we will thoroughly review the statistical reference framework by presenting a set of tools to identify clusters of industries in the space. Specifically in Sect. 2 we will concentrate on the bivariate version of Ripley's (1977) K function. In Sect. 3 we will discuss the system of hypotheses at the basis of the identification of clusters and by distinguishing two possible null hypotheses to be contrasted with the hypothesis of spatial clustering of industries. Section 4 is devoted to an empirical application of the bivariate K function in the study of the inter-sectoral location of innovation in Italy based on a dataset of the European Patent Office (EPO). Finally Sect. 5 contains some conclusions and directions for further developments in the field.

2 The statistical theoretical framework: bivariate K functions

Univariate K-functions (proposed by Ripley 1976, 1977) have been already used in economic geography to characterize the geographical concentration of industries (see e.g., Arbia and Espa 1996; Marcon and Puech 2003a; Quah and Simpson 2003). In this paper we will consider a bivariate extension of such a method to describe spatial clusters of pairs of firms. Although the approach could be straightforwardly generalized to an arbitrary number of, say, $g(g > 2)$ industries, in this paper we will deliberately restrict ourselves to the bivariate case for the sake of illustrating the methodology. The method is based on a bivariate functional of distance t (that we will refer to as $K_{ij}(t)$) which characterizes the joint spatial pattern of points or, more precisely, the spatial relationships between two typologies of points located in the same study area: for instance firms belonging to two different industrial sectors, say Type i and Type j. The bivariate K function is defined as follows:

$$K_{ij}(t) = \lambda_j^{-1} E\,\{\#\text{ of points of Type } i \text{ falling at a distance} \leq t \text{ from an arbitray Type } j \text{ point}\} \quad (1)$$

with $E\{.\}$ indicating the expectation operator and the parameter λ_j representing the intensity of Type j point process, that is the number of Type j points per unitary area. Obviously, in the presence of a multivariate point process we have g typologies of events and, consequently, g^2 bivariate K functions that is: $K_{11}(t), K_{12}(t), \ldots, K_{1g}(t)$, $K_{21}(t), K_{22}(t), \ldots, K_{2g}(t), \ldots, K_{gg}(t)$. In the remainder we will distinguish between univariate and bivariate K functions by calling *auto-functions* the K functions when $i = j$ and *cross-functions* those when $i \neq j$. Conversely, when $i = j$, $K_{ii} = K_i$ represents the more traditional univariate auto-function K used in the economic analysis by e.g., Quah and Simpson (2003) and Marcon and Puech (2003a) and Duranton and Overman (2005)

In Eq. 1, the term $\lambda_j K_{ij}(t)$ represents the expected number of Type j points falling within a circle of radius t centred on an arbitrary Type i point. Symmetrically we interpret the bivariate function $K_{ji}(t)$ in such a way that $\lambda_i K_{ji}(t)$ represents the expected number of Type i points falling within a circle of radius t centred on an arbitrary Type j point. Similarly to the case of univariate K function, also the bivariate K function is built under the assumption of isotropy (Arbia 2006) that is the case when no directional bias occurs in the neighbourhood of each point.

In a bivariate point map constituted by, say, n_i points of Type i and n_j points of Type j within an area A, we can define a class of estimators of the cross-functions K by close analogy to those suggested in the univariate case (Ripley 1977; Diggle 1983).

To start with, let us consider the indicator function:

$$I_{lk}(t) = \begin{cases} 1 & \text{if} \quad d_{lk} \leq t \\ 0 & \text{if} \quad d_{lk} > t \end{cases}$$

where d_{lk} represents the distance between the lth Type i point and the kth Type j point. If no border effects are present, then the non-parametric estimator of the cross-function $K_{ij}(t)$ can be expressed as:

$$\hat{K}_{ij}(t) = \left(\hat{\lambda}_i \hat{\lambda}_j A\right)^{-1} \sum_{l=1}^{n_1} \sum_{k=1}^{n_2} I_{lk}(t)$$

where A is the total surface of the area, $\hat{\lambda}_i = \frac{n_i}{A}$ and $\hat{\lambda}_j = \frac{n_j}{A}$.

Analogously, by inverting the role between Type i and Type j points, the corresponding non-parametric estimator for the cross-function $K_{ji}(t)$ is given by:

$$\hat{K}_{ji}(t) = \left(\hat{\lambda}_i \hat{\lambda}_j A\right)^{-1} \sum_{l=1}^{n_2} \sum_{k=1}^{n_1} \nu_{lk}^{-1}(t) J_{lk}(t)$$

with $\nu_{lk}(t)$ and $J_{lk}(t)$ analogous to the $I_{lk}(t)$ functions in the previous expression.

If the generating random field is stationary and isotropic (Arbia 2006), then $K_{ij}(t)$ should be equal to $K_{ji}(t)$. However, due to possible border effects[2] and to the asymmetry of the related corrections, $\hat{K}_{ij}(t)$ and $\hat{K}_{ji}(t)$ will be not exactly equal although strongly correlated. A more efficient (although not absolutely efficient) estimator is thus the one proposed by Lotwick and Silverman (1982) given by:

$$K^*_{ij}(t) = \frac{\hat{\lambda}_j \hat{K}_{ij}(t) + \hat{\lambda}_i \hat{K}_{ji}(t)}{\hat{\lambda}_i + \hat{\lambda}_j} \tag{2}$$

Likewise Ripley's univariate K function, also in the case of the multivariate functions we can introduce the L transformation proposed by Besag (1977) that is characterized by a more stable variance. In the bivariate case the $\hat{L}_{ij}(t)$ functions assume the following expressions:

$$\hat{L}_{ij}(t) = \sqrt{\hat{K}_{ij}(t)/\pi}$$

and

$$\hat{L}_{ji}(t) = \sqrt{\hat{K}_{ji}(t)/\pi}$$

where the functions are linearized dividing by π and the square root stabilizes the variance.

Similarly to Eq. 2 we can consider the Lotwick–Silverman transformation:

$$L^*_{ij}(t) = \frac{\hat{\lambda}_j \hat{L}_{ij}(t) + \hat{\lambda}_i \hat{L}_{ji}(t)}{\hat{\lambda}_i + \hat{\lambda}_j} = \sqrt{K^*_{ji}(t)/\pi}$$

which produces more efficient estimators of the L function.

3 The basic hypotheses of the model: spatial independence or random labelling?

In this section we wish to introduce various alternatives offered in the spatial statistical literature to specify the null hypothesis of absence of regularities in the location of pairs of points in space. These will represents our counterfactuals in the subsequent empirical analysis reported in Sect. 4.2. In order to correctly interpret the estimates provided by $K^*_{ij}(t)$ and $L^*_{ij}(t)$ to test the null hypothesis of absence of spatial interaction, traditionally the empirical estimates are compared with simulated envelopes. The reference framework for such tests is provided by Barnard (1963) and adapted by Ripley (1979) to the case of univariate spatial clusters. In the case of bivariate patterns the specification of the null hypothesis is more complicated. In fact we can have two possible definitions depending on the nature of the case examined: a null of

[2] On "border effects" and corrections for them see e.g., Ripley (1981). Explicit expressions of the correction factors in the case of irregular study areas are derived in Goreaud and Pélissier (1999).

independence and a null of *random labelling* (Diggle 1983; Dixon 2002). The choice between the two alternatives can strongly affect the final results and can lead to wrong conclusions. However, this distinction is often ignored in the literature where the univariate procedures are sometimes uncritically applied (among the few exceptions see Diggle 1983 and, more recently Dixon 2002; Goreaud and Pélissier 2003). The two cases will now be discussed in some details.

3.1 The null hypothesis of independence

According to a first specification of the null hypothesis the two typologies of points on the map can be conceived as two populations and the resulting spatial pattern can be interpreted a priori as the outcome of two distinct point random fields. In this situation the absence of interaction between the two components corresponds to the lack of interaction between the two generating fields. In other words, the location of points generated by the field related to Typology i is independent of the location of points generated by the field related to Typology j (Lotwick and Silverman 1982). Under this hypothesis, therefore, we have that $K_{ij}(t) = \pi t^2$. We will refer to this first null hypothesis as to the "hypothesis of independence" and we will indicate it with the symbol H_0^1.

If within the circle of radius t centred on an arbitrary Type i point we record the presence of more Type j points than we expect under H_0^1, then $K_{ij}(t) > \pi t^2$ which represents the surface of a circle of radius t. Such a result indicates a positive dependence between the two components and, hence, the presence of *agglomeration* between the two generating fields. In contrast, if within the circle of radius t centred on an arbitrary Type i point we record the presence of less Type j points than expected under H_0^1, then $K_{ij}(t) < \pi t^2$, thus indicating *repulsion* (or *inhibition)* rather than agglomeration. The confidence band to run formal hypothesis testing procedures at the various distances can be built through Monte Carlo simulation (Besag and Diggle 1977; See also Ripley 1977; Goreaud and Pélissier 2003 for details).

3.2 The null hypothesis of random labelling

According to a second specification of the null hypothesis each of the two components depend on some factors that a posteriori produce a differentiation between the two typologies of points. In the case of economic data, such factors can be identified in a set of explanatory variables encouraging location of industries at a certain point in space and producing a different pattern in the two typologies of points. For instance they might refer to a differentiated system of taxes and incentives encouraging location of Type i point while discouraging location of Type j points. We will refer to this second hypothesis as to the "random labelling" and we will indicate it with the symbol H_0^2. The general reference framework in this second instance is that of the so-called *marked point processes* (see, e.g., Diggle 1983) that is point processes where not only the location of each object is reported, but also an extra characteristics that differentiates between them (e.g., small and large firms, presence or absence of an innovation etc.)

Let the spatial structure of the indistinct generating process for the two typologies of points be synthesized by the univariate K auto-function (Ripley 1977):

$$\lambda K(t) = E\{\text{\# points within a circle of radious } t \text{ around each point in a map}\}$$

where $\lambda = \frac{n}{A}$ represents the density and $n = n_1 + n_2$.

Under H_0^2, the ratio $p_j = \frac{n_j}{n}$ represents the probability of belonging to Typology j. Then we have that $p_j \lambda K(t) = \lambda_j K(t) = \lambda_j K_{ij}(t)$ so that $K_{ij}(t) = K(t)$. If within the circle of radius t centred on an arbitrary Type i point there are more Type j points than expected under H_0^2, then $K_{ij}(t) > K(t)$. This result indicates that at distance t the two components tend to be positively dependent, thus revealing the presence of *agglomeration*. On the contrary, if within the circle of radius t centred on an arbitrary Type i point there less Type j points than expected under H_0^2, then $K_{ij}(t) < K(t)$ which indicates the presence of a negative dependence between the two components or *inhibition*. Again the confidence bands can be generated via Monte Carlo simulation.

When H_0^2 holds true, we have that all the bivariate K functions (both the two auto-functions and the two cross–functions) are equal to the univariate K function of the map where there is no distinction between the two components so that $K_{ij}(t) = K_{ji}(t) = K_{ii}(t) = K_{jj}(t) = K(t)$. Operationally the departures from the null of *random labelling* could be evaluated by computing the pair-wise differences between the various K functionals and by comparing them with the simulated confidence bands (see Diggle and Chetwynd 1991; Gatrell et al. 1996; Kulldorff 1998; Dixon 2002; Haining 2003).

It is important to observe that the two alternatives for the null hypothesis considered in this section describe in statistical terms the usual distinction made in quantitative geography between two otherwise undistinguishable effects: the effect of spatial interaction between agents and the effect of spatial reaction to common factors (Cliff and Ord 1981). Both effects give rise to observed regularities in space. They also mirror from a certain view angle the distinction made by some authors in the economic literature between joint-localization and co-localization (see e.g., Duranton and Overman 2005).

4 Characterizing the spatial distribution of innovations in Italy 1995–1999

4.1 Descriptive analysis

The empirical analysis focuses on the use of the EPO dataset containing all patent applications made at European Patent Office (established by Monaco's Convention) starting from 1978. In particular we use the version elaborated at CESPRI, Bocconi University, Milan. The dataset provides us with information about petitioners, inventors, request date, International Patent Classification code (distinguishing the various industrial sectors), and citations among patents. The use of the inventors' residence allows us to localize exactly each patent (Arbia et al. 2008). In our database we omitted Sicily, Sardinia and the other Italian islands because of the lack of spatial continuity with the main land. This lack of continuity could produce serious biases in our

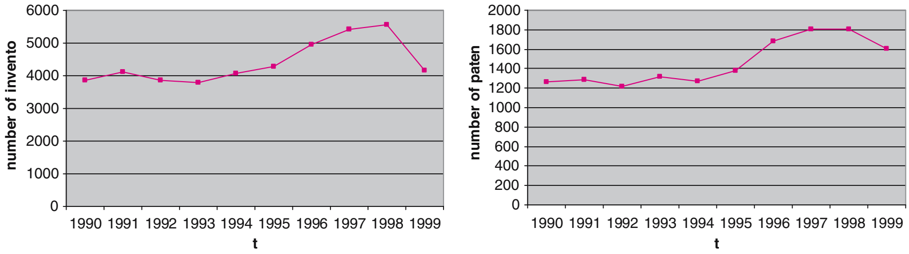

Fig. 1 **a** Inventors with at least 1 invention and **b** mono-inventors in the period 1990–1999. Source: European Patent Office data processed at CESPRI, Bocconi University, Milan and at the Department of Economics, University of Trento

procedures that are based on Euclidean distances. The resulting dataset consists of 44,078 inventors, but only 25,312 patents due to the presence of multi-inventors patents. To avoid any subjectivity in the assignment of a unique location to each patent, we considered only patents with one single inventor that amount to 14,632 in our database. We left to future further refinements the problems related to the spatial assignment of patents with multiple inventors. The patents are classified within six industrial sectors, namely: *Electricity Electronics* ($S1$), *Instruments* ($S2$), *Chemical Pharmaceutical* ($S3$), *Process Engineering* ($S4$), *Mechanical Engineering Machinery* ($S5$) and *Consumer Goods Civil Engineering* ($S6$). In our database we also avail temporal information related to two different moments of time of the registration of each patent, namely: (i) the publication date and (ii) the priority date, that is the date of the earliest filling of an application made in one of the patent offices adhering to the convention. The choice of one date or the other is crucial because the time lag between the priority date and the publication date may range from 1.5 to 2.5 years. We chose the latter because it is the date that gets closer to the actual timing of the patented invention.

In the modelling phase, we restrict our attention to the most recent years and so we employed only data based on the aggregation of the last 5 years (from January 1995 to December 1999). The dynamic is totally absent in the present analysis and it is our intention to extend the analysis in a future study to a space–time context by exploiting the statistical literature on "space–time" K-functions introduced by Diggle (1993) and Diggle et al. (1995).

Figure 1 reports the yearly time series of the 44,078 inventors submitting for patents at EPO (Fig.1a) and those that are mono-inventors in which case the spatial location of inventors and patents are the same (Fig.1b). The selected period 1995–1999 coincides with an evident period of increase in the volume of inventors.

With reference to the same dataset Table 1 reports the sectoral distribution of patents with just one inventor in the period 1995–1999. By distinguishing each patent in terms of its specific industrial sector we can interpret our data as a single realization of a multivariate spatial point process. The map reported in Fig. 2 displays the overall spatial distribution of the 8,279 cases.

The map reveals a clear agglomeration pattern of the points within some *innovative* regions, namely Milan's area in the centre–north and the north-eastern part of the country. Indeed, the whole northern regions are very innovative and contain more than

Table 1 Frequency distribution of the number patents with only one inventor distinguished by industrial sector in the periods 1995–1999

Sectors	Number of patents (1995–1999)
Electricity electronics = $S1$	951
Instruments = $S2$	831
Chemical pharmaceutical = $S3$	675
Process engineering = $S4$	1,302
Mechanical engineering machinery = S5	2,830
Consumer goods civil engineering = $S6$	1,690
Total	8,279

Source: European Patent Office data processed at CESPRI, Bocconi University, Milan and at the Department of Economics, University of Trento

Fig. 2 Location of 8,279 patents in Italy in 1995–1999. Source: European Patent Office data processed at CESPRI, Bocconi University, Milan and at Department of Economics, University of Trento

66% of the total number of patents. Conversely the central part of Italy contains only about the 30%, of the patents with a remarkable concentration around Rome and Florence, and only 4% of the patents are located in the southern regions. These empirical findings are not surprising considering the well-known industrial gap existing between Italian regions and, specifically the dualism between the north and the south of the country. Also, the recent literature on knowledge spill-overs and specifically the research that concentrated on patent citation (Jaffe et al. 1993; Breschi and Lissoni 2001, 2006; Driffield 2006) provides persuasive explanation for the observed geographical pattern. The same kind of information is contained in the graphs reported in Fig. 3 displaying the frequency distribution of inventors (Fig. 3a) and the ratio of the number of investors to the number of individuals aged 15–65 in 1999 (Fig. 3b).

In particular Fig. 3b shows that the higher concentration observed in the north cannot be due to population concentration and reveals a genuine prevalence of inventors in that area.

It is helpful to disaggregate the previous map into as many point processes as the number of industrial sectors, each one characterised by a different intensity. To help visualizing this aspect Fig. 4 reports the point map for each sector. The same feature

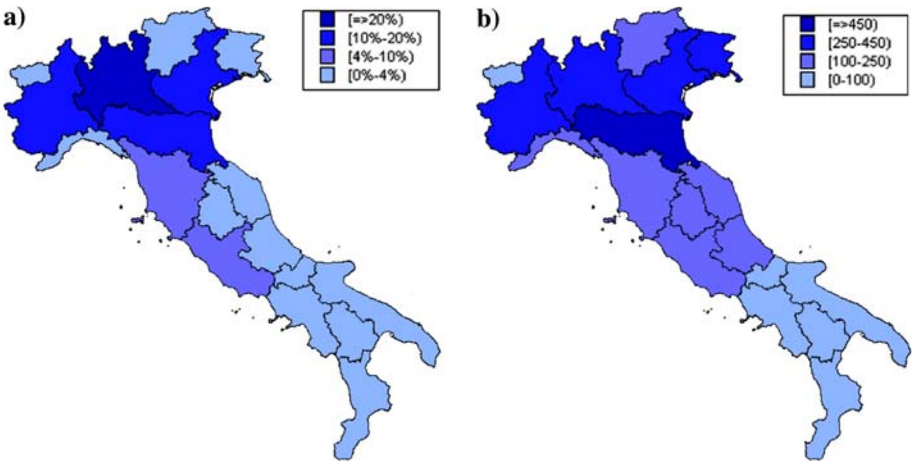

Fig. 3 Regional distribution of patents in Italy in the period 1995–1999. **a** Number of patents, **b** patents per 1,000 inhabitants. Source: Istat and European Patent Office data elaborated at CESPRI, Bocconi University, Milan and at Department of Economics, University of Trento

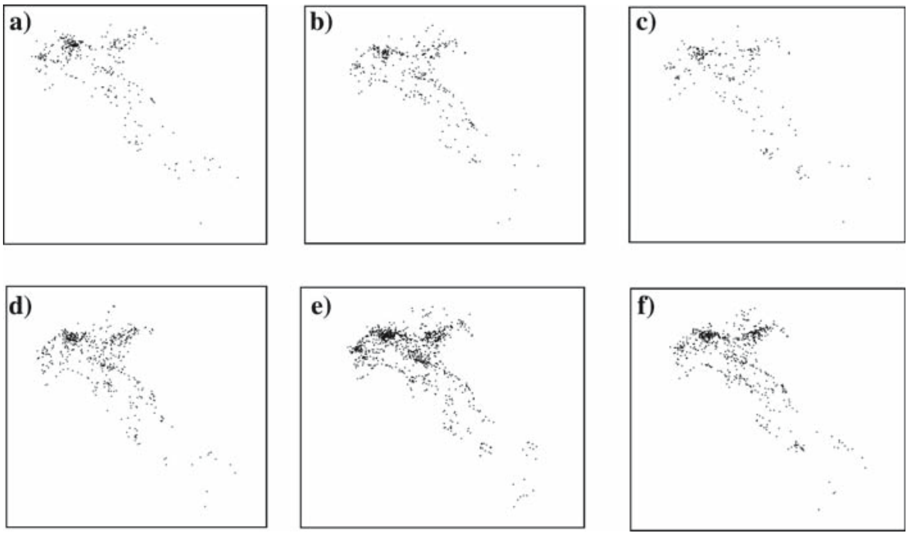

Fig. 4 Location of 8,279 patents in Italy in 1995–1999 distinguished by sector. Source: European Patent Office data elaborated at CESPRI, Bocconi University, Milan and at Department of Economics, University of Trento. **a** Electricity Electronic, **b** Instruments, **c** Chemical Pharmaceutical, **d** Process Engineering, **e** Mechanical Engineering Machinery, **f** Consumer goods Civil Engineering

of higher concentration in the north appears evident for all six sectors considered. Indeed, the observed geographical patterns are very similar for the six sectors with evident concentrations around the main industrial northern towns (Milan and Turin). Some minor, but still evident, concentrations can be observed around Bologna and Venice for patents of the *Process Engineering*, *Mechanical Engineering Machinery* and *Consumer goods Civil Engineering* sectors and on the east coast between Rimini

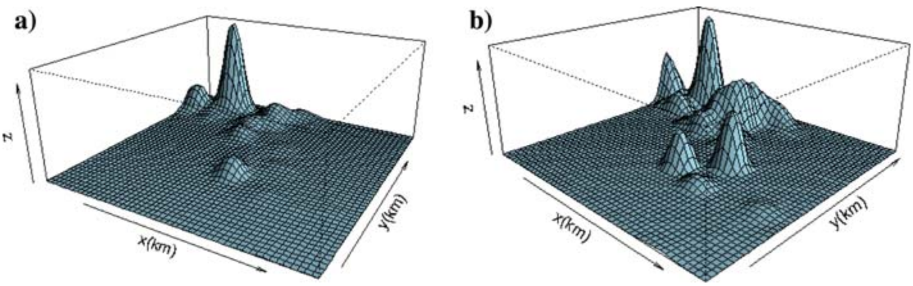

Fig. 5 Kernel estimation of the spatial density of the two point process .The bandwidth parameter is set to $\tau = 50$ km. **a** Electricity Electronics, **b** Instruments

and Ancona for the patents of the sector *Consumer goods Civil Engineering* (see Fig. 4f).

4.2 Modelling the joint location of patents

In this section we will first of all illustrate with a certain detail the method used for estimating the bivariate K functions. For the purpose of illustrating the estimation method we will concentrate on the spatial interaction between patents of the *Electricity Electronics* sector and those of the *Instruments* sector. For all other pairs of sectors we will only report the results of the estimation procedures. In order to perform an exploratory analysis of the spatial patterns of points, we initially converted the maps displayed in Fig. 4 into spatial densities by using a non-parametric kernel estimator. Figure 5 shows, for the two sectors of *Electricity Electronics* and *Instruments*, the kernel density estimation of the random process, say $\lambda(s)$, $\boldsymbol{s}$ representing the vector of coordinates of the points, $\boldsymbol{s} \in \Re^2$. For the estimation we considered the following quadratic kernel (see Hastie and Tibshirani 1990; Fan and Gijbels 1996)

$$\hat{\lambda}_\tau(s) = \sum_{d_j<\tau} \frac{3}{\pi\tau^2}\left(1 - \frac{d_j^2}{\tau^2}\right)^2 \tag{3}$$

where τ represents the *bandwidth* (that is the parameter controlling the smoothness of the surface), d_l is the distance between point $\boldsymbol{s}$ and the event located at point s_l and the summation refers to all distances $d_j < \tau$.

Interesting insights in terms of exploring the relationships between the two sectors are obtained by superimposing the two maps of points reported in Fig. 4a, b. In order to do this we exploited the following kernel estimator:

$$\hat{\lambda}_{\tau;i/1+2}(\boldsymbol{s}) = \frac{\hat{\lambda}_{\tau;i}(\boldsymbol{s})}{\hat{\lambda}_{\tau;1+2}(\boldsymbol{s})}, \quad i = 1, 2$$

where both $\hat{\lambda}_{\tau;i}(\boldsymbol{s})$ and $\hat{\lambda}_{\tau;1+2}(\boldsymbol{s})$ were computed using expression (3). We will refer to this kernel estimation as to a *dual kernel.*

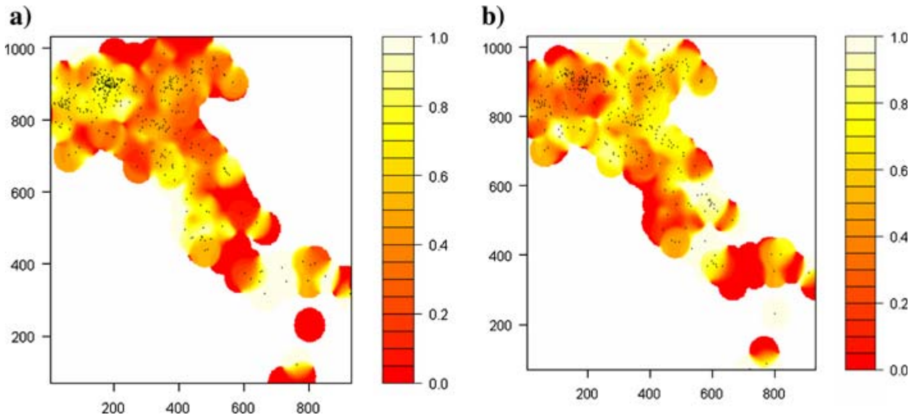

Fig. 6 Dual kernel estimation of the spatial density. The bandwidth parameter is $\tau = 35$ km. **a** Electricity Electronics, **b** Instruments

Figure 6a, b display the output of the estimation procedure obtained for the joint distribution of the *Electricity Electronics* and *Instruments* sectors. In particular in Fig. 6a we display with a different shading the dual measures ranging from 0 (when there are only patents of sector *Instruments*) to the value of 1 (in the cases where there are only patents of the *Electricity Electronics* sector). A darker shading in Fig. 6a reveals the prevalence of patents of the *Electricity Electronics* sector whereas Fig. 6b displays the complementary information for the *Instruments* sector. In both graphs intermediate values in the scale allows us to identify areas where both sectors are present. Similar graphs were derived for all other pairs of sectors, but they are not reported here since they do not add particular insights.

Concerning the identification of the bivariate map it seems more grounded the hypothesis of *random labelling* with respect to that of *independence* (see Sect. 3) in that the labelling of the patents to a certain sector occurs in a subsequent moment with respect to the moment of the deposit at the EPO. In the remainder of this section we will report the estimation results of the different bivariate versions of the K function that can be used to study the joint location of all pairs of sectors.

To start with, Fig. 7 reports the behaviour of the L^* function for the two sectors *Electricity and Electronics* and *Instruments*. Similar graphs have been derived for all other pairs of sectors, but they are not reported here in that they display very similar behaviours.[3] The effect of co-agglomeration is evident for all pairs of sectors at all distances in that all graphs lay entirely above the diagonal that represents the case of random labelling. Thus points are more clustered than expected under the null hypothesis of random labelling.

In order to investigate more closely this effect of co-agglomeration significant insight can be gained by inspecting the behaviour of the K cross-functions. In fact, as already said, under the null hypothesis of random labelling we have that

[3] All graphs are available upon request from the authors or can be accessed directly on the website. http://www.springerlink.com/content/102505/.

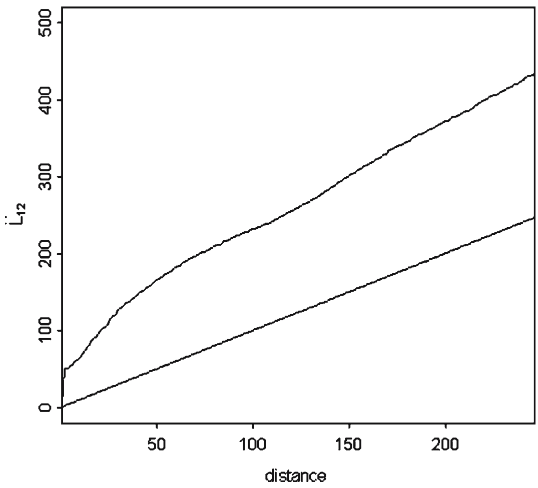

Fig. 7 Behaviour of the functional statistics $L^*_{ij}(t) = \sqrt{K^*_{ij}(t)//\pi}\ \forall i, j = 1, 2, \ldots, 6$ for the two sectors *Electricity*-it Electronics and *Instruments*. In the graph the diagonal represents random labelling. All points above the diagonal represent agglomeration, whereas all points below the diagonal represent repulsion

$K_{ij}(t) = K_{ji}(t) = K_{ii}(t) = K_{jj}(t) = K(t)$ so that all bivariate K functions (both the *auto*-functions and the *cross*-functions) coincide with the univariate K function obtained by merging together the two sectors in one map.

In order to test formally the null hypothesis, we need to explicitly choose a functional measuring the departure from the random labelling hypothesis. A first obvious choice is the simple difference between the two functionals $\hat{K}_{ii}(t) - \hat{K}_{jj}(t)$. However, as suggested by Diggle and Chetwynd (1991), such a function can only help in evaluating the clustering of objects and it is less useful when we want to discern the mutual spatial relationships between the two components. A better solution is offered by the differences $\hat{K}_{ii}(t) - K^*_{ij}(t)$ and $\hat{K}_{jj}(t) - K^*_{ji}(t)$ that are more informative with respect to the problem in hand. In fact when $\hat{K}_{ii}(t) > K^*_{ij}(t)$ and $\hat{K}_{jj}(t) > K^*_{ji}(t)$ both patents labelled i and j display a tendency to spatial segregation within mono-type clusters.

The graphs reported in Fig. 8 display the behaviour of the functionals $\hat{K}_{ii}(t) - K^*_{ij}(t)$ and $\hat{K}_{jj}(t) - K^*_{ji}(t)$ respectively, at the various distances for some selected pairs of sectors. In these figures we also report the Monte Carlo confidence bands referred to the null H^2_0 at a significance level $\alpha = 0.05$. The horizontal lines in the graphs represent the null hypothesis of random labelling.[4]

The visual inspection of Fig. 8 suggests in most cases the lack of random labelling, but with remarkably differentiated patterns.

[4] The critical levels to test the null H^2_0 at 5% significance were obtained as follows. First of all we simulate $N_{sim} = 1{,}000$ maps in which the bivariate vector of the patents is randomized conditionally upon the number of points of Sector i (n_i) and of sector j (n_j) and upon the coordinates $\mathbf{x}$ of the total n_{ij} points ($n_{ij} = n_i + n_j$). Local robust estimators (at each distance t) of the upper and the lower limit of the confidence band for the differences $\hat{K}_{ii}(t) - K^*_{ij}(t)$ and $\hat{K}_{jj}(t) - K^*_{ij}(t)$ are then obtained by selecting the $N_{sim}\frac{\alpha}{2}$ and (respectively) the $N_{sim}\left(1 - \frac{\alpha}{2}\right)$ order statistics of the 1,000 estimates. The choice of $N_{sim} = 1{,}000$ was dictated by Martens et al. (1997) that suggested as a practical rule a number of simulations such that $\alpha N_{sim} < 5$. The choice of $N_{sim} = 1,000$ is consistent with Duranton and Overman (2005).

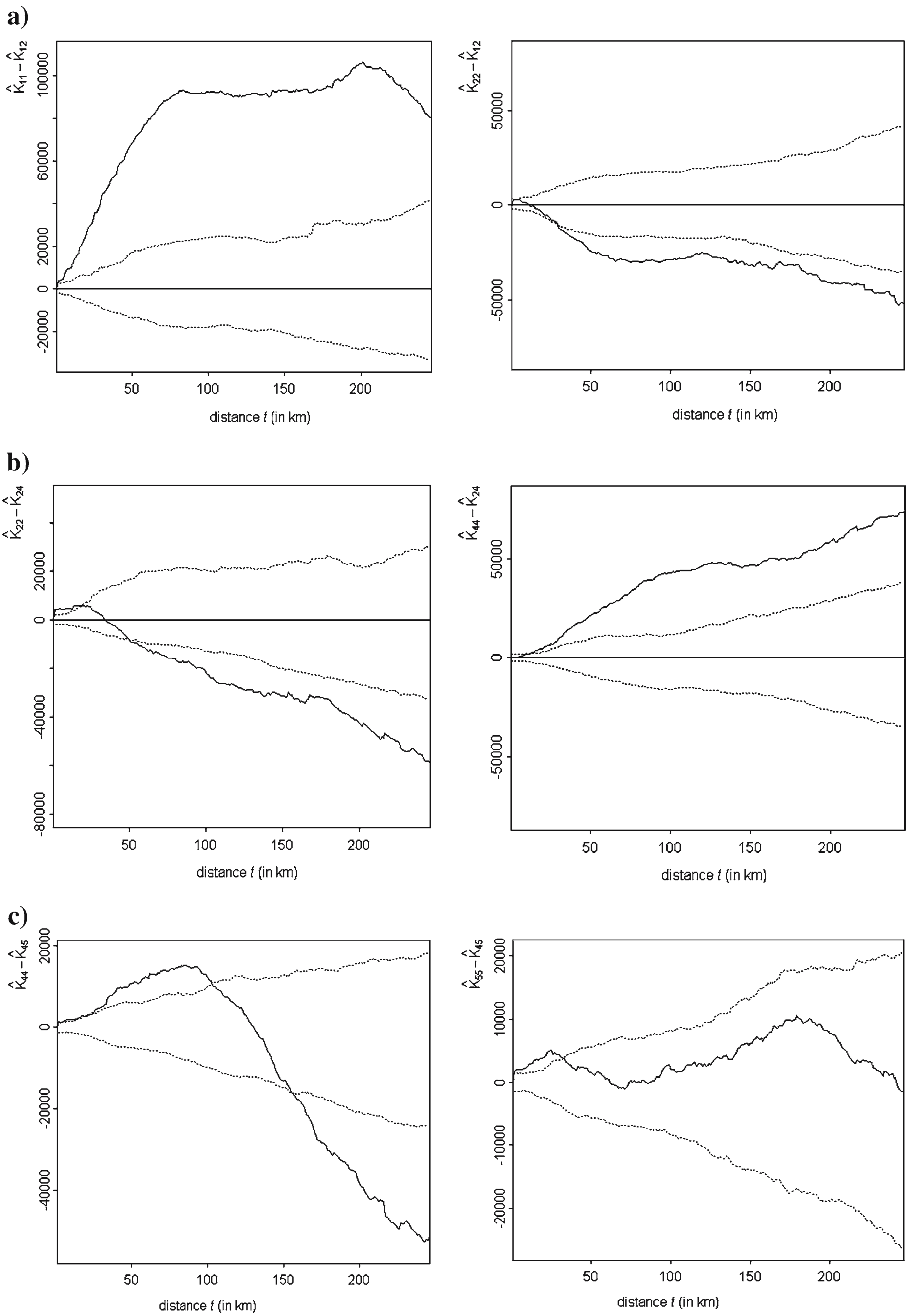

Fig. 8 Behaviour of the functional statistics $\hat{K}_{ii}(t) - K^*_{ij}(t)$ and $\hat{K}_{jj}(t) - K^*_{ij}(t)$ (*solid line*) and of the corresponding 0.025 and 0.975 quantiles (*dashed lines*) estimated on the basis of 1,000 simulated random labelling. Reference to causality is represented by the *horizontal line*. **a** Electricity-Electronics versus Instruments, **b** Instruments versus Process Engineering, **c** Process engineering versus Mechanical Engineering Machinery

Let us start commenting on Fig. 8a that refers to the joint pattern of location of the *Electricity Electronics* and *Instruments* sectors. The graphs of the functional $\hat{K}_{11}(t) - K^*_{12}(t)$ in Fig. 8a is always above the $K = 0$ horizontal line and is above the bands at 95% confidence level thus indicating significant attraction at all distances. In contrast the graph of the functional $\hat{K}_{22}(t) - K^*_{12}(t)$ suggests random labelling at small distances ($t < 30$ km) with the line falling entirely within the 95% confidence bands. Conversely, at higher distances, the graph falls in the lower part of the confidence bands suggesting repulsion between the two sectors.

As a consequence the location of points referring to the two industrial sectors cannot be considered as randomly labelled, rather they display an interesting pattern of attraction–repulsion. The patents of the *Electricity Electronics* sector tend to locate close to patents of the same sector, whereas patents of the *Instruments* sector display (at small distances below 30 km) a tendency to locate in the neighbourhood of patents of *Electricity Electronics*. Such a gravitational effect is dominated by an internal segregation effect (above the mentioned threshold of 30 km) that prevents the patents of the *Instruments* sector to constitute patches. In summary: points of *Electricity Electronics* tend to cluster on one another while point of *Instruments* display a repulsion on one another and an attraction towards those of *Electricity Electronic*. The first effect thus confirms Marshall–Arrow–Romer theoretical expectations (Marshall 1890; Arrow 1962; Romer 1986) and Porter's idea of dynamical externalities generated by specialization (Porter 1990). The second effect follows from the dynamic externalities *à–la–Jacobs* arising from industrial diversification (Jacobs 1969). By commenting jointly Figs. 7 and 8 we observe that the reciprocal aggregation effect between the *Electricity Electronics* sector and the *Instruments* sector suggested by the behaviour of the function $L^*_{12}(t)$ in Fig. 7, is not the same in both directions and it appears to be led by the *Electricity Electronic* sector. From an economic point of view such a results can be easily interpreted by observing that the *Instruments* sector includes goods whose production requires technologies linked to the *Electricity Electronics* sector. Thus the knowledge flows generated by firms of the *Electricity Electronic* sector produce a benefit to the neighbouring industries of the sector of *Instruments*. In contrast the *Electricity Electronics* sector includes goods whose production does not require technologies linked to the *Instruments* sector that most likely benefits from internally generated knowledge flows.

In our work we derived the graphs of the functionals $\hat{K}_{ii}(t) - K^*_{ij}(t)$ and $\hat{K}_{jj}(t) - K^*_{ji}(t)$ for all 15 possible pairs of the 6 sectors considered. However here we report only some selected cases due to lack of space.[5] By examining all possible pairs of sectors we can identify four different typologies of attraction–repulsion.

The most common typology observed is the one that we have described into details when commenting on the relationships between the *Electronic Engineering* and the *Instruments* sectors. In fact this pattern is very similar to that displayed by the *Electricity and Electronics* sector on one side and the sectors *Instruments*, *Chemical Pharmaceutical*, *Process Engineering* and *Mechanical Engineering Machinery* on the

[5] Again, as for the case reported in Fig. 7, the graphs related to all pairs of sectors are available on the website http://www.springerlink.com/content/102505/.

other. A similar pattern is also displayed by the pair constituted by *Instruments* versus *Chemical Pharmaceutical* and, with some minor differences, by the pairs involving the *Chemical Pharmaceutical* sector on one side and *Instruments, Process Engineering, Mechanical Engineering Machinery* and *Consumer goods Civil Engineering* sectors on the other side.

In this first dominating typology we observe clusters of points of one sector at small distances (between 30 and 50 km) co-existing with points of the second sector that are internally over-dispersed. At high distances points of the second sector become randomly labelled. Only in the case of the relationships between the sector of *Chemical Pharmaceutical* and *Mechanical and Civil Engineering*, we observe a tendency to cluster after 100 km. It is, however, important to remember that at these higher distances the number of points on which the estimation is based decreases dramatically and thus the estimates are less reliable due to the lack of degrees of freedom. This first typology well describes the stylized facts suggested by Duranton and Overman (2005).

A second typology of attraction–repulsion is displayed by the pairs of sectors involving the relationships between the *Instruments* sector on one side and the sectors of *Process Engineering*, *Mechanical Engineering Machinery* and *Consumer Goods and Civil Engineering* on the other. As an example of this second typology, Fig. 8b displays the case of *Instruments* versus *Process Engineering*. Here the pattern displays clusters on one sector at small distances (less than 20 km) attracting a second sector that is also self-clustered. At higher distances we conversely observe segregation.

A third typology is displayed by the pairs of points referring to the relationships between the *Process Engineering* sector on one side and the *Mechanical Engineering Machinery* and *Consumer goods Civil Engineering* sectors on the other. Figure 8c displays the case of *Process Engineering* versus *Mechanical Engineering Machinery* as an example of such typology. Here we notice a tendency to cluster for the points of one sector that also produces a strong attraction on the points of the other sector. At high distances (more than 150 km) we conversely observe repulsion in the pattern of the first sector. The effect of concentration of points of the first sector is persistent at all distances in the case of the patents of the *Mechanical engineering Machinery* sector versus those of the *Consumer goods Civil Engineering* sector.

Finally we have a residual typology where we can classify the exceptions to the three typologies described above. These exceptions are represented by the patterns displayed by *Electricity Electronics* versus *Chemical Pharmaceutical* and by *Process Engineering* versus *Consumer goods Civil Engineering*. In the first instance we observe clusters of one sector at small distances co-existing with a second sector that appears to be randomly labelled. In the second instance we have clusters of both sectors only at intermediate distances ranging between 120 and 160 km.

4.3 Controlling for the underlying industrial concentration

The functionals considered in the previous section can help in identifying bivariate clusters of firms, but they consider the space as homogeneous with all portions of space having a priori the same probability of hosting a point. Conversely the economic space is highly heterogeneous. On these basis Ellison and Glaeser (1997) suggest that, when looking at the location patterns of firms, the null hypothesis should be that of spatial randomness, but only conditional upon both industrial concentration and overall agglomeration. Their index satisfies this requirement. Similarly Maurel and Sedillot (1999) and Devereux et al. (2004) develop indices with similar properties. Duranton and Overman (2005) notice that "*unevenness does not necessarily mean an industry is localized*" and translate these consideration into the formal requirement that "*any informative measure of localization must control for industrial concentration*" (p. 1078; see also Sect. 1 and Footnote 5). They go further in suggesting that not all points in the space can host a new point and requiring that "*the set of all existing sites currently used by a manufacturing establishment constitutes the set of all possible locations for any point"* (p. 1085). In this last section we wish to introduce the use of the bivariate K functions to fulfil Ellison–Glaeser requirement and we compare for each sector the actual pattern with the pattern generated by all patents considered as a whole. More in details we compute the differences between the bivariate K function for each sector on one side and the univariate K function computed considering all sectors together. Such a difference can help in identifying sectors that are over-concentrated (over-dispersed) not in absolute terms as in the traditional univariate K analysis (Marcon and Puech 2003a), but conditionally upon the spatial pattern displayed by the other firms for the economy as a whole. Of course we are aware that, for this analysis to be complete, we should consider the spatial pattern of all firms in the economy, but in the empirical analysis reported here we restrict ourselves to only the pattern of patents included in the EPO database to have at least some indications.

Figures 9a–f report the results of this analysis based on the functional $\hat{K}_{ii} - \hat{K}_{tt}$, $\hat{K}_{tt}$ representing the K function referred to the all patents considered as a whole. We have also computed the functionals $\hat{K}_{tt} - \hat{K}_{it}$, but they are not reported here because they provide very similar information.[6]

The exam of Fig. 9 reveals some interesting features. First of all, the patents of the *Electricity Electronics* and *Chemical Pharmaceutical* sectors display at all distances over-concentration with respect to the underlying global concentration of patents (see Fig. 9a, c). In particular *Electricity Electronics* presents high and increasing concentration up to 80 km whereas *Chemical Pharmaceutical* presents the maximum concentration at around 60 km and then a decreasing pattern and even randomness after 160 km. Such results parallel those of Duranton and Overman (2005) that found localization mostly at small scales (less than 60 km) and a general tendency for *Chemical Pharmaceutical* products to over-clustering.

Secondly, the *Instruments* sector displays over-dispersion with respect to the underlying distribution of patents at distances greater than 50 km. Thirdly, the patents of the *Process Engineering* sector display a more complex pattern with significant over-clustering only in the interval between 70 and 140 km. Finally the *Mechanical Engineering Machinery* and the *Consumer goods Civil Engineering* sectors display random labelling at all distances (remember that estimates at high distances are less reliable due to the lack of degrees of freedom). Therefore in these two sectors there

[6] These graphs, likewise those related to Figs. 7 and 8, are available at the website. http://www.springerlink.com/content/102505/.

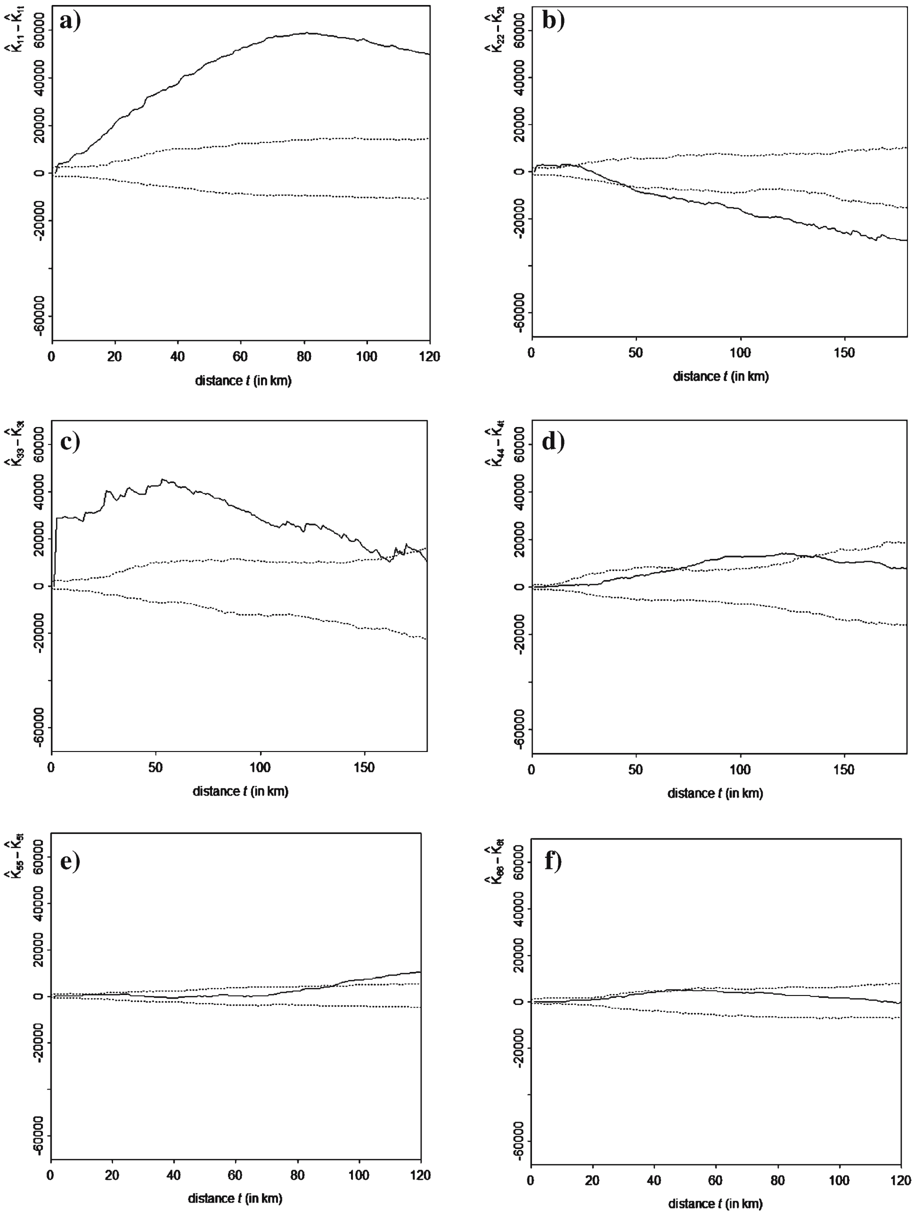

Fig. 9 Behaviour of the functional statistics $\hat{K}_{ii}(t) - \hat{K}_{tt}(t)$ (*solid line*) and of the corresponding 0.025 and 0.975 quantiles (*dashed lines*) estimated on the basis of 1,000 simulated random labelling. Reference to causality is represented by the *horizontal line*. Points above the 0.975 quantiles denote significant agglomeration of points of one sector around points of all other sectors. Points below the 0.025 quantiles denote significant repulsion of points of one sector from points of all other sectors. **a** Electricity Electronics, **b** Instruments, **c** Chemical Pharmaceutical, **d** Process Engineering, **e** Mechanical Engineering Machinery, **f** Consumer goods Civil Engineering

seems to be no specific tendency to either clustering of repulsion apart from those that are characteristic of the economy as a whole.

5 Summary and concluding remarks

In this paper we extended the use of Ripley's (1977) K functions previously considered in the economic literature by Arbia and Espa (1996), Quah and Simpson (2003), Marcon and Puech (2003a) and Duranton and Overman (2005) to the analysis of the joint spatial pattern of industries.

By applying a methodology based on the bivariate cross-functions K to the spatial distribution of patents in Italy in the period 1995–1999, we have been able to discern quite distinct geographical patterns for the six sectors considered.

Our main findings are the following:

- The pattern displayed by the patents of all pairs of the six sectors considered is always of agglomeration when analysed in absolute terms looking at the standard bivariate K functions.
- However, when looking more closely at the pair-wise relationships between the six sectors considered, a more differentiated situation emerges. In fact, most of the observed joint patterns (precisely 8 of the 15 pairs of sectors considered) display a situation of dominance of one sector on the other. This dominance assumes that there is a leading sector that is clustered in space at small distances (up to 50 km) and a second sector that is dispersed internally and clustered around the leader. In particular this is the pattern displayed by the patents of the *Electricity Electronics* and the *Chemical Pharmaceutical* sectors that act as leaders with respect to the other sectors.
- Such a specificity of the *Electricity Electronics* and the *Chemical Pharmaceutical* sectors emerges also when considering the analysis of agglomeration conditional on the global concentration of patents in the economy as a whole. In fact, in this case, the mentioned sectors are the only two that present over-clustering with respect to the general pattern of all patents. In particular we notice a climax at around 80 km for the patents of the *Electricity Electronics* sector and at around 60 km for the patents of the *Chemical Pharmaceutical* sectors. Conversely for the patents belonging to the other sectors we record over-dispersion for the *Instruments* sectors and no significant departure from randomness in the remaining sectors.

The analysis considered here has shown the importance, but also the limits of a static approach and the necessity to introduce temporal dynamics in order to reconstruct the whole process of individual choices behaviour. Thus an important step forward in the application of the spatial econometric techniques discussed here is represented by the introduction of the time dimension. In fact the analysis of the static bivariate K functions registers only the situation in one definite period of time and provides only a single snapshot of the whole dynamic process. Quite obviously, this snapshot can be of help in suggesting the generating mechanism of individual locational choices as it is realized in a dynamic context like a single photogram reveals something about the nature of the movie it is drawn from. For instance, the individual choice behaviour of firms suggested by Fig. 8a could be interpreted as the process through which in a first moment industries of one sector (say Type 1) locate themselves in the space at random and industries of another sector (say Type 2) tend to locate around them to exploit technological and physical spillovers. If new Type 1 industries locate in the area, they tend to locate away from Type 2 industries creating a buffering zone that can be due to physical or economic constraints. This behaviour seems to suggest a leading position of Type 1 industries with respect to Type 2. This dynamic, however, describes only one of the possible behaviours, and more refined *spatial laws of motion* could be suggested by the analysis of proper dynamic K functions.

The theoretical basis for considering dynamic spatial patterns in economic analysis are well depicted by Quah and Simpson (2003). Dynamic "space–time" K-functions (Diggle 1993; Diggle et al. 1995) can be conceived as functionals depending on both spatial distances and the time lag which indicate how many points characterized by a certain label fall within a certain distance of other points after a certain period of time. Such an analysis would greatly help the study of the concentration of industries and the analysis of diffusion processes which, in turn, are issues of tremendous importance when analysing sectoral growth and the rise and fall of regions within one country. Since understanding the dynamics of the spatial distribution of firms can also help to clarify the complex mechanisms of international trade, the development of this field appears to be as one of the most challenging in the future research agenda.

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