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Detecting the existence of space–time clustering of firms

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ABSTRACT

The use of the *K*-functions (Ripley, 1977) has recently become popular in the analysis of the spatial pattern of firms. It was first introduced in the economic literature by Arbia and Espa (1996) and then popularized by Marcon and Puech (2003), Quah and Simpson (2003), Duranton and Overman (2005), and Arbia et al. (2008). In particular in Arbia et al. (2008) we used Ripley's *K*-functions as instruments to study the inter-sectoral co-agglomeration pattern of firms in a single moment of time. All this research has followed a static approach by disregarding the time dimension. Temporal dynamics, on the other hand, play a crucial role in understanding the economic and social phenomena particularly when referring to the analysis of the individual choices leading to the observed clusters of economic activities. With respect to previous contributions to the literature, this paper uncovers the process of firm demography by studying the dynamics of localization through space–time *K*-functions. The empirical part of the paper will focus on the study of the long run localization of firms in the area of Rome (Italy), by concentrating on the *Information and Communication Technology* (*ICT*) sector data collected by the Italian Industrial Union in the period 1920–2005.

1. Introduction: The spatial–temporal analysis of clusters of firms

There is no question that the process of localization of firms in space is essentially a dynamic phenomenon. At the centre of the observed spatial patterns of clustering (where firms tend to attract each other) or inhibition (where firms tend conversely to repulse each other), we always find considerations related to time, dynamics, lagged dependence and evolution. In fact we cannot study phenomena like firm demography, birth–death processes and growth in space if the time dimension is disregarded. Yet the study of the clustering of firms in space and time has stubbornly followed two separated paths. On the one hand, there is a long tradition of a substantial number of techniques available for modelling clustering of firms in time based on purely time series methods and on the analysis of business cycles (Hamilton, 1994). These techniques may assist in the identification of situations of time concentration where we observe a higher number of new firms in some particular periods due to cyclical movements or trends. On the other hand, research on spatial clustering of economic activities is more recent and it originated from a reinterpretation of Marshall's insights on 19th-century industrial localization by some authors in the nineties (e.g. Krugman, 1991; Fujita et al., 1999). Following these seminal works the empirical analysis of spatial clusters has developed along two distinct lines of research. The first was an attempt to directly examine the underlying economic mechanism using the spatial dimension only as a source of data (see e.g. Ciccone and Hall, 1996; Jaffe et al., 1993; Rauch, 1993; Henderson, 2003). The basic methodology here is that of a panel data or pure spatial regressions that employ observable covariates related to space (Arbia, 2006; Baltagi, 2008). The second line of research attempts to characterize the spatial distribution of economic activities by observing the joint behaviour of the different units distributed across space (Devereux et al., 2004; Duranton and Overman, 2005; Ellison and Glaeser, 1997; Ioannides and Overman, 2004); the reference methodology is that of the spatial point pattern analysis (Diggle, 2003). In this field the use of the *K*-functions (Ripley, 1977) has become popular. First introduced in the economic literature by Arbia and Espa (1996), it was then popularized by Marcon and Puech (2003), Quah and Simpson (2003), Duranton and Overman (2005) and Arbia et al. (2008). In particular Arbia et al. (2008) proposed the use of Ripley's *K*-functions as an instrument to study the inter-sectoral co-agglomeration pattern of firms in a single moment of time.

The analysis of clusters in space and time has thus followed two different paths and two separate methodologies with no interactions between them. Time series methods have generally disregarded the

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spatial dimension while spatial clustering models have been essentially static and have only analysed the outcome of the dynamic adjustments as it is observed in one single moment of time. This approach is obviously partial and doomed to leave a number of different empirical cases that may occur in practice without explanation. In fact new firm settlements may display no spatial concentration if we look separately at each moment of time and yet they may present a remarkable agglomeration if we look at the overall resulting spatial distribution after a certain time period.

The importance of taking into account the temporal dynamics when analysing spatial patterns of events have been well explained by Getis (1964), and Getis and Boots (1978). In the latter work, the authors refer to a straightforward "framework for viewing spatial processes" and argue that without knowing the temporal evolution of the phenomenon under study it is not possible to identify the mechanism generating its spatial structure. In particular, they show that different space–time processes can lead to resulting spatial patterns which look the same. As a consequence, only phenomena which exhibit no increase or decrease of points over time might be represented as pure spatial processes (Getis and Boots, 1978) and hence could be meaningfully analysed neglecting the time dimension.

With respect to the contributions which previously appeared in the literature, this paper attempts to unify the two approaches and to uncover the process of firm demography in a more comprehensive way by tackling it, both from a spatial and temporal point of view, within a unified framework. This framework is provided by the theory of space–time *K*-functions which evolved as an extension of the simple synchronic *K*-function (introduced in Ripley, 1976) and of the so-called second-order analysis of point patterns (see Getis and Boots, 1978). Examples of applications may be found in regional science (Feser and Sweeney, 2000, 2002), geography (Getis, 1983; Okabe et al., 1995; Yamada and Rogerson, 2003) and ecology literature (Goreaud and Pélissier, 1999, 2003).

In the epidemiological context, Diggle et al. (1995) have proposed an extension of the spatial univariate *K*-function to allow for the detection of space–time interactions in what was termed a *time-labelled spatial point pattern*. Our purpose is to introduce this statistical framework in the context of economic geography to study the interactions between the spatial and temporal distributions of firms. Specifically, we intend to test empirically the presence of the space–time clustering of firms. Once the significance of the space–time clustering phenomenon is assessed by using the space–time *K*-function approach, we will be in the position to test the presence of hypothetical spatial configurations like leader–follower patterns or the presence of spatial segregation between 'old' and 'young' industries.

In order to assess the scientific scope of our proposed methodology we need to clarify preliminarily what we mean by "spatial cluster of firms". The notion of spatial concentration we refer to in the present context is the "topographic concentration", as defined by Brülhart and Traeger (2005), which evaluates the geographic distribution of economic activities only relative to physical space. In this context, the absence of a concentration benchmark is represented by a spatial pattern where the firms are randomly spread over the physical space. Therefore, the departures from this random spatial diffusion are considered as clusters without taking into account the spatial distribution of exogenous variables like traffic accessibility, factor endowments, skills and labour force potential. In other words, in the present context the spatial component of the space–time clustering phenomenon can be jointly determined by the interactions among economic agents–driven, for example, by the presence of knowledge spillovers or external economies of scale–and the exogenous features of the territory — such as the presence of useful infrastructure, the proximity to communication routes or the possibility to benefit from public incentives to locate in specific areas outside the residential centres. However, the firms that we refer to in the case study considered in Section 3 belong to the *Information and Communication Technology* (*ICT*) sector and–unlike, for example, the agricultural and heavy manufacturing industries–they do not need particularly weighty endowments. Therefore, we can reasonably argue that the first factor, rather than spatial heterogeneity, is prevalent in driving clusters.

The structure of the paper is the following. In Section 2 we will introduce the methodological framework and we will present the theory of the space–time *K*-functions. To assist the interpretation of the subsequent empirical analysis, in this section we will also describe some stylized spatial distributions of firms that may occur in empirical cases and the corresponding behaviour of the *K*-functions diagnostics. Section 3 will be devoted to the empirical part of the paper by first introducing the working dataset based on the spatial distribution of ICT firms in the area of Rome (Italy) collected by the Industrial Union in the period 1920–2005. It will also contain the empirical application of the models presented in Section 2 based on this dataset. Section 4 contains the discussion of the results and the analysis of their economic implications. Finally, Section 5 contains some concluding remarks and directions for future developments in this field.

2. The statistical methodological framework

2.1. Space–time K-function analysis

Economic events, such as the establishment of new firms, may occur at different points in space and time. Consequently, in order to study the geographic concentration of industries we should check for the temporal dynamics that characterize the localization processes. Accordingly, we need to explore the possibility that the spatial and temporal phenomena, producing the observed pattern of firms at a given moment of time, interact to provide space–time clustering. This requirement can be performed by a statistical test regarding the independence between the spatial and the temporal distribution of firms. In the case of dependence, the geographic pattern of firms is characterized by the presence of space–time interaction meaning that such a pattern cannot be explained only by static factors but that we should also consider the dynamic evolution of the spatial concentration phenomenon.

Univariate spatial *K*-functions (proposed by Ripley, 1976, 1977) have already been used in the economic literature to detect the geographical concentration of industries (see e.g., Arbia and Espa, 1996; Marcon and Puech, 2003; Quah and Simpson, 2003). They can be exploited in a dynamic context by analysing separately the spatial and the temporal clustering pattern. However, a more comprehensive approach refers to the analysis of both dimensions simultaneously thus also paying attention to the space–time interactions. In this paper we will consider a dynamic extension of the univariate *K*-functions proposed and fully described in Diggle et al. (1995). In what follows we will present a brief account of the theory of space–time *K*-functions. The symbolism and definitions are in accordance with those used in Arbia et al. (2008) to which the reader is referred for the simple purely spatial *K*-function.

Generally speaking, the technique involves the comparison between the observed spatio-temporal point pattern and a theoretical pattern that has the same temporal and spatial properties as the original data but no space–time interaction (Diggle et al., 1995; French et al., 2005). In this context auxiliary information is associated with every observed spatial point in the form of the time of occurrence. Under the assumption of stationarity and isotropy (Diggle, 2003; Arbia, 2006), we can build up the space–time *K*-function:

$$\lambda_{DT}K(d,t) = E\{\#\text{ of points falling at a distance and a time respectively } \leq d \text{ and } t \text{ from an arbitrary point}\} \quad (1)$$

(French et al. 2005), with $E\{\cdot\}$ indicating the expectation operator and the parameter λ_{DT} representing the spatial and temporal joint intensity of the point process i.e. the number of points per unitary area and per unit time. If the processes working in time and space are independent (i.e. if there is no space–time interaction) the functional $K(d,t)$ should be equal to the product of the spatial and temporal K-functions $K_D(d)K_T(t)$ (Diggle et al., 1995), where $K_D(d)$ and $K_T(t)$, are defined respectively as follows:

$$\lambda_D K_D(d) = E\{\#\text{ of points falling at a spatial distance} \le d \text{ from an arbitrary point}\} \tag{2}$$

and

$$\lambda_T K_T(t) = E\{\#\text{ of points falling at a time interval} \le t \text{ from an arbitrary point}\}.$$

In the previous expressions λ_D represents the spatial intensity i.e. the number of points per unitary area. In a similar fashion λ_T denotes the temporal intensity i.e. the number of points per unit time. The meaning of a univariate spatial K-function ($K_D(d)$) is well known (see Ripley, 1977 and Arbia et al., 2008 for economic interpretation). They suggest visually if the firms tend to concentrate significantly in some portions of the study area rather than in others. Purely temporal K-function ($K_T(t)$) is not treated in the statistical literature but could be used to identify if in the observed time series, a significantly higher number of firms is concentrated in some periods rather than in others.

In the case of no space–time interaction we might theoretically expect that $K(d,t) = K_D(d)K_T(t)$ (Diggle et al., 1995; Gatrell et al., 1996). In fact, the product-functional $K_D(d)K_T(t)$ represents the expected K-function under the hypothesis of the absence of space–time interaction and can be used as a reference for comparison with the observed space–time K-function, $K(d,t)$.

By investigating estimation aspects from a univariate 'time marked' point map, we can define the estimators of the three component processes (i.e. $K(d,t)$, $K_D(d)$ and $K_T(t)$) by close analogy to those suggested in the unmarked univariate case (Ripley, 1977; Diggle, 2003).

First we will consider the space–time K-function which, as we mentioned above, is represented by the expected number of points within a spatial distance d and a time interval t of an arbitrary point scaled by the expected number of points per unitary area and per unit time. Diggle et al. (1995) have shown that a proper edge-corrected estimator of $K(d,t)$ from an observed 'time marked' point pattern with n observations can be the following:

$$\hat{K}(d,t) = \frac{AT}{n^2}\sum_i \sum_{j\neq i} \frac{I_d(d_{ij})I_t(t_{ij})}{w_{ij}v_{ij}}$$

where A is the total surface of the area and T is the whole observed interval of time. In addition the terms d_{ij} and t_{ij} represent the spatial distance and the time interval between the ith and jth observed points. Finally, $I_d(d_{ij})$ and $I_t(t_{ij})$ represent indicator functions assuming the value 1 if $d_{ij} \le d$ and $t_{ij} \le t$ respectively, and 0 otherwise.

Due to the presence of spatial and temporal edge effects (which might potentially distort the estimates close to the boundary of the area A and to the time limits of T) the adjustment factors w_{ij} and v_{ij} are introduced. The weight function w_{ij} expresses the proportion of the circumference of a circle centred on point i, passing through the point j, which lies within A (Boots and Getis, 1988). By analogy, the factor v_{ij} refers to the time segment centred on i, of length t_{ij}, lying within the observed total duration time between 0 and T (Diggle, 2003; Diggle et al., 1995; Gatrell et al., 1996).

Referring to the same statistical framework, the edge-corrected estimators of the spatial and temporal K-functions, $K_D(d)$ and $K_T(t)$ are defined respectively as:

$$\hat{K}_D(d) = \frac{A}{n^2}\sum_i \sum_{j\neq i} \frac{I_d(d_{ij})}{w_{ij}}$$

(Boots and Getis, 1988; Diggle, 2003) and:

$$\hat{K}_T(t) = \frac{T}{n^2}\sum_i \sum_{j\neq i} \frac{I_t(t_{ij})}{v_{ij}}$$

(Diggle et al., 1995; Bailey and Gatrell, 1995). As already stated, when there is no space–time interaction we find that $K(d,t) = K_D(d)K_T(t)$. As a consequence, one possible exploratory tool for the independence between the processes operating in time and space is the functional:

$$\hat{D}(d,t) = \hat{K}(d,t) - \hat{K}_D(d)\hat{K}_T(t) \tag{3}$$

(Gatrell et al., 1996). This functional is proportional to the increased numbers of points within spatial distance d and time interval t with respect to a process which possesses the same temporal and spatial characteristics but no space–time interaction. As a consequence, the presence of space–time interactions might be revealed in the appearance of peaks on the 3-dimensional surface of $\hat{D}(d,t)$ plotted against the spatial distance and the time sequence.

Diggle et al. (1995) and French et al. (2005) have proposed a transformation of Eq. (3) which allows for the possibility of working with relative quantities rather than absolute numbers. This is defined as:

$$\hat{D}_0(d,t) = \hat{D}(d,t) / \{\hat{K}_D(d)\hat{K}_T(t)\} \tag{4}$$

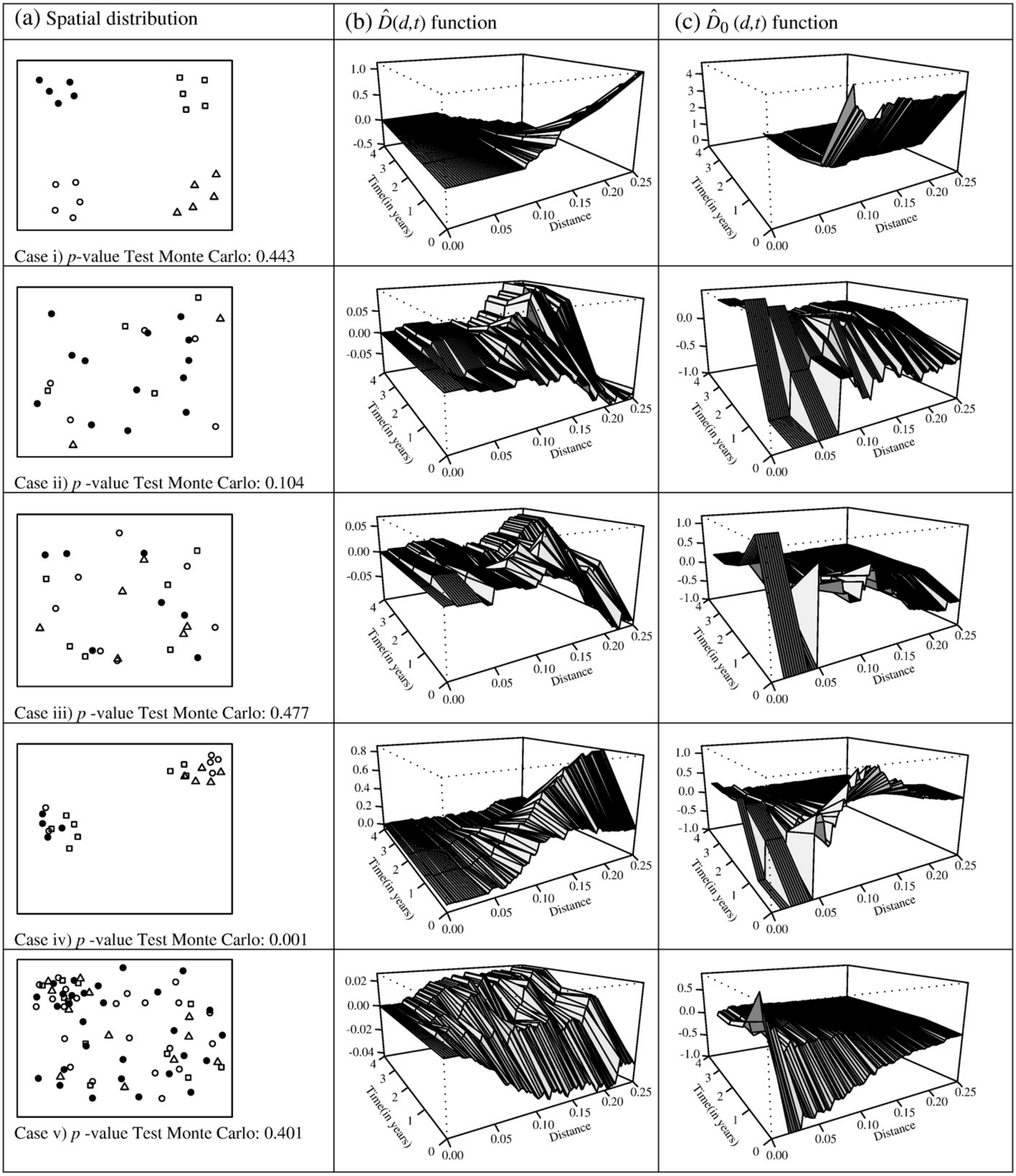
Expression (4), the "Diggle function", is proportional to the relative increase in points within spatial distance d and time interval t with respect to a process with the same temporal and spatial characteristics but no space–time interaction. Similarly to $\hat{D}$, the functional $\hat{D}_0$ can be plotted in a 3-dimensional graph versus d and t to help the visualization and the detection of interdependence between the spatial and temporal processes.

As stated at the beginning of this section, the K-functions-based empirical method quantifies explicitly the spatial dependence between events under the working assumption of spatial homogeneity (or stationarity). This is expressed by the fact that in Eqs. (1) and (2) the spatio-temporal joint intensity and spatial intensity (λ_{DT} and λ_D) respectively are assumed as constant. A natural way to overcome this procedural limit consists of allowing these two quantities to vary over space. We could express these two functions as $\lambda_D(x)$ and $\lambda_{DT}(x)$, where the argument x represents the geographic coordinates of an arbitrary point. We followed the approach in Arbia et al. (2009a,b)–limited to the mere spatial perspective and hence neglecting the temporal evolution–to analyse the spatial interactions among firms of the high-tech industry in Milan while controlling for the exogenous effects of the characteristics of the study area. One of the primary tasks of the future research agenda in the subject under investigation will be that of extending this analytical procedure to the temporal perspective in order to develop a method to assess the space–time clustering phenomenon in an inhomogeneous spatial and temporal environment.

2.2. Some stylized space–time distributions

Before introducing the important aspects related to the inferential evaluation of space–time interaction, it is useful to present some stylized situations that may occur in empirical cases when observing the spatial distribution of firms. The examination of these extreme paradigmatic situations and the analysis of the corresponding behaviour of the K functionals will assist the interpretation of the functionals $\hat{D}(d,t)$ and $\hat{D}_0(d,t)$ in the case study that will be analysed in Section 3.

Fig. 1 reports some theoretical spatial distributions of firms and the corresponding diagnostic plots. These could be used as benchmarks to be compared with the empirical situations that may be observed in



NOTES: Case i): Spatial clustering, no time clustering, no space-time interaction
Case ii): No spatial clustering, time clustering, no space-time interaction
Case iii): No spatial clustering, no time clustering, no space-time interaction.
Case iv): Spatial and time clustering and space-time interaction.
Case v): Spatial and time clustering, no space-time interaction.
For the meaning of the p-value Monte Carlo test see the discussion in Section 2.3. p-values larger than 0.05 refer to non significant space-time interaction. Figures a) are based on only few points to help the visualization. Figures b) and c) are based on a larger number of simulatedpoints.

Legend

Symbol	Year
●	1
□	2
○	3
Δ	4

Fig. 1. Some theoretical spatial arrangements of firms in space and time (column a) and the corresponding $\hat{D}(d,t)$(column b) and $\hat{D}_0(d,t)$ plots (column c). Space is represented by a unit square. Time is represented by the set [14]$\in N$.

practical instances. In doing so we follow an approach that has already proved useful in a study by Getis (1964) on the changes in the commercial land-use pattern. In the quoted paper the author derives a series of stylised spatial point patterns built under different economic hypotheses of birth, death and diffusion and then tries to identify the pattern that is closer to the observed distribution.

Fig. 1 describes only a few examples and it is certainly not exhaustive of all the cases that may be found in practice. We need to clarify that the distributions reported in column a) of the figure are stylized simplified arrangements based on only a few points and are used only to clarify the five extreme situations. In contrast, the graphs reported in columns b) and c) are not based on the same points as displayed in column a) as these latter were insufficient to interpolate the 3-D graphs meaningfully but were obtained through simulations based on a much larger number of points. Notice that the time dynamics in these examples is partially masked by the fact that we do not consider the death of firms but only the process of new firm creation.

Case i) refers to the instance of *clustering in space with no clustering in time and no space–time interaction*. The map appears with a strong visual impression of clustering in each time period but the number of newly founded firms is constant over time (see the different time symbols in the maps) thus displaying no time concentration. The situation is represented by a flat $\hat{D}_0(d,t)$ function in the time direction and a peak at a distance of 0.06 in space. Case ii) refers to the opposite situation where we do have *clustering in time but no clustering in space and no interaction*. In this case the visual impression is that of spatial randomness both in each time period taken individually and as a whole but the number of firms in some periods is significantly higher than in others with, in particular, a strong concentration of new firms in the first time period. This situation is revealed in the graph c) with a peak of the $\hat{D}_0(d,t)$ function in time at lag 2 and an (almost) flat function on the spatial axis. Case iii) refers to the case of *no space, no time clustering and, as a result, no interaction* and has the appearance of no clustering in space with new firms that are created randomly in the different time periods. The $\hat{D}_0(d,t)$ function here is flat in both the space and time direction. Case iv) considers the instance where points are *clustered both in time and space with an interaction* between the two dimensions. Graph a) presents points that are highly agglomerated in space if observed in each individual time period and also if we look at all points jointly disregarding the different time markers. In this graph a strong time concentration with a higher number of new firms created in the second time period is also evident. Finally, Case v) considers the situation where points are *clustered both in time and space but there is no interaction* between the two dimensions. Observing each year individually produces a visual impression of clustering; however, looking at the whole map without distinguishing between the different time periods the visual impression is that of randomness. There is also a considerably high degree of time concentration with a higher number of new firms created in the first time period. This situation was generated artificially by considering the product of the two marginal *K*-functions in space and time separately.

It is important to stress that the purpose of the proposed methodology is to discriminate if the observed space–time pattern of economic activities is driven by a systematic mechanism or purely by chance. We argue that this is an important first step in the analysis of space–time dynamics of firms. In fact if the location pattern is primarily due to randomness, then any economic model trying to explain the observed pattern would be meaningless. As a consequence we argue that the use of the proposed tools is preliminary to the detection of the relevant economic factors that determined the observed spatial configuration. This second important step, however, could only be tackled with different tools and with a larger information set on structural variables other than just the geographic location, such as the plant size, the characteristics of the local demand and the workforce market potential. For these reasons this second step is not undertaken here and is left for future study.

Obviously any substantive conclusions on the prevailing spatial and time pattern cannot be based merely on the visual inspection of the empirical graphs contrasted with the stylized pattern and they need a more grounded validation based on sound inferential tools. These tools will be introduced in the following section.

2.3. Inference

In this section we will introduce an inferential framework in order to formally assess the significance of the empirically observed values of $\hat{D}(d,t)$. However, since the exact distribution of the functional D is unknown, its variance cannot be evaluated theoretically and no exact statistical testing procedure can be adopted. To overcome this aspect Diggle et al. (1995) suggested in obtaining a significance test by exploiting a Monte Carlo approach. In the quoted paper the authors performed m simulations, where at each step the n geographical points are marked at random with the observed n time 'markers'. Having thus obtained m simulated spatial–temporal point patterns, we can then compute m different estimates of $\hat{D}(d,t)$. We will refer to these estimates with the symbol $\hat{D}_i(d,t)$, $i=1,\ldots,m$. The observed variance of these m estimates, for example $\hat{V}(d,t)$, can be reasonably used as an estimator of the variance of $\hat{D}(d,t)$ (Gatrell et al., 1996). Having introduced these definitions, we can also introduce the idea of "standardized residuals" as

$$\hat{R}(d,t) = \hat{D}(d,t) \,/\, \sqrt{\hat{V}(d,t)}. \tag{5}$$

The term "standardized residuals" is the one used in the literature, as suggested by Diggle et al. (1995), and refers to the ratios between the observed values of $\hat{D}(d,t)$ and its estimated standard deviation reported in Eq. (5). However, the use of this term may be misleading since it has nothing to do with the meaning more commonly assigned to it in regression analysis. In practice, it represents the excess number of points of $\hat{K}(d,t)$ with respect to $\hat{K}_D(d)\hat{K}_T(t)$ and it is a measure of space–time interaction. In the absence of any space–time interaction, these residuals have zero expectation and a variance equal to one. Therefore, an appropriate inferential method to test if the spatial and temporal processes are independent of one another consists in plotting the graph associated with Expression (5) against the product-functional $\hat{K}_D(d)\hat{K}_T(t)$. If there is no space–time interaction then approximately 95% of the values of $\hat{R}(d,t)$ would lie within two standard errors (French et al., 2005). The interpretation of the $\hat{R}(d,t)$ plot is not always straightforward; it could be masked by the fact that the residuals could be strongly dependent. In addition to this test, a further overall Monte Carlo testing procedure of space–time clustering has been suggested. It consists in taking the actual observed sum of the functionals $\hat{D}(d,t)$ overall d and t and making a comparison with the empirical distribution of the m analogous sums of $\hat{D}_i(d,t)$ overall d and t, $(i=1,\ldots,m)$. A particularly high value of the observed sum among the values of this 'artificial' distribution would constitute evidence of overall space–time interaction. For example, as Gatrell et al. (1996) pointed out, if the observed sum is ranked above 95 out of 100 simulated values then the probability that the observed space–time interaction occurred by pure chance is less than 5%.

3. Analysing the long run spatial dynamics of firms: The case of ICT industries in Rome (Italy) 1920–2005

3.1. Economic background: Theoretical expectations for ICT firms' location in cities

In the last few years there has been a flourishing of studies on the increase of a *knowledge-based economy* (OECD 1996, 2001; Drucker, 1998; Foray, 2000; David and Foray, 2003; Cooke et al., 2007) and a number of spatial economic theories can be found in the literature on industrial agglomeration which can help in postulating the expected location patterns of ICT firms.

At the risk of oversimplifying the discussion, and without claiming to exhaust the vast literature on the subject, we can distinguish between at least two broad lines of thought.

According to a first consistent part of the literature, one should expect the ICT firms to be spatially concentrated within the big metropolitan areas. Indeed, the idea of a strong connection between spatial clusters and economic performance where knowledge matters significantly has a very long tradition that can be traced back to the seminal contributions of Marshall (1920), and to the following re-appraisal of Perroux (1950), Hirschman (1958) and Jacobs (1961). Fundamentally the expectation of clustering of the ICT firms is supposed to be driven by the so-called *tacit knowledge* (Nonaka and Takeuchi, 1995; Polanyi, 1966) assuming the knowledge to be transferable only through direct *face-to-face* interaction (Storper and Venables, 2003). However, the new forms of technological knowledge are usually tacit, in the sense that their accessibility is bound by the geographic proximity of high-technology firms or knowledge institutions and by the nature and extent of the interactions among these actors in an innovation system (Lambooy and Van Oort, 2005). Therefore, the knowledge spillovers should be more easily picked up in cities, where many specialized workers are concentrated into a relatively small limited space and where the transmission of new knowledge tends to occur more efficiently by direct human interaction (Glaeser et al., 1992; Henderson et al., 1995; Dumais et al., 2002; Van Oort, 2004; Lambooy and Van Oort, 2005). The role of geographical and cultural proximity for tacit knowledge exchange has been discussed extensively in the literature on high-technology clusters (Saxenian, 1994; Storper, 1997, 2002; Porter, 1998; Keeble and Wilkinson, 2000; Yeung et al., 2007) and *innovative milieux* (Capello, 1999; Rallet and Torre, 1999).

In contrast, according to a second line of research primarily lead by the works of Sassen (1994), Castells (1996) and Cairncross (1997 and 2001), we should expect the ICT firms to locate without a significant spatial structure. Essentially, these authors argue that the rapid development of the communication technologies in the 90's (and in particular the advent of the internet) has limited the role of space in the locational choices of economic agents. As a consequence the exchange of knowledge and information is now less dependent on physical flows within the geographical space than it used to be in the past due to the increased possibility of communicating in real time with any point in the world.

Thus, the economic theory suggests at least two different location phenomena characterizing the ICT industry: one leading to spatial concentration, the other driving to geographic patterns where spatial interactions among economic agents are irrelevant.

In the following sections we will try to assess the empirical relevance of these two competing lines of thought by studying the spatial configuration of the ICT industries in the metropolitan area of Rome. In Section 3.2 we will present the database and in Section 3.3 we will make use of the space–time methodology illustrated in Section 2 to test whether the spatial and temporal distributions are dependent and if there is any space–time interaction in the locational choices of ICT firms.

3.2. Data description

The empirical part of this paper focuses on a set of micro data on the firms in the ICT sector in Rome. This dataset has been collected over a fairly long period ranging from 1920 to 2005 by the Industrial Union of Rome (UIR). The large time span considered could, in principle, create problems in the classification of industries that may have changed over time. However in the ICT sector, the firms that were still operating in 2005 could have changed their denomination but not the typology of their product which remained constant over time. The dataset reports the full address and the year of establishment of the 169 industries currently operating in the area, thus disregarding those established in the period considered but which did not survive. The ICT industries are further classified into two groups: *Electronic and Communication* (*C*) and *Information Technology* (*IT*). In our database there are 66 firms belonging to the first group and 103 to the second group. Table 1 reports the time evolution of the sector in the 85 years considered in terms of the number of firms set up in each decade. The slow development of the sector until the early eighties and the more pronounced increase in the birth of new companies in the eighties and in the nineties is evident. The dynamics are very similar for the Electronic and Communication and the Information Technology sectors.

Table 1
Frequency distribution of the number of firms by year of establishment.

Year of establishment	Number of firms		
	(1) Electronic and Communication	(2) Information Technology	(3) ICT = (1) + (2)
1920–1960	5	0	5
1961–1970	5	1	6
1971–1980	4	10	14
1981–1990	15	30	45
1991–2000	29	37	66
2001–2005	8	25	33
Total	66	103	169

The spatial distribution of the 169 firms in the ICT sector is reported in Fig. 2, which also provides an idea of the dynamics by marking with different symbols the firms established in the different decades. Data are available at the finest level of time and spatial resolution as the full address and the exact date of registration are accessible and it is only for the purpose of illustration that they have been temporally grouped into decades in Table 1 and Fig. 2.

Fig. 2a reports the spatial distribution of the entire ICT sector. It is clear from a first visual inspection of the diagram that data display a marked tendency to cluster by concentrating in some specific portions of space, namely the central part of the area and particularly near the city centre. Different graphical symbols are used to illustrate the temporal dynamics. However, in Fig. 2a the number of points is too large to display any definite time pattern which can be easily identified on purely visual considerations and this requires further and more sophisticated analysis. The tendency to cluster is rather different in the two groups. By looking at the different graphical symbols, in the case of Fig. 2b due to the limited number of points reported (only 66), we can also notice a certain tendency of firms to locate in space near industries existing in previous time periods thus revealing evidence of space–time interaction.

This preliminary descriptive analysis clearly indicates that the observed pattern is characterized by a distinctive spatially and temporally localized process, but with remarkably different features in the two groups of firms which need further investigation.

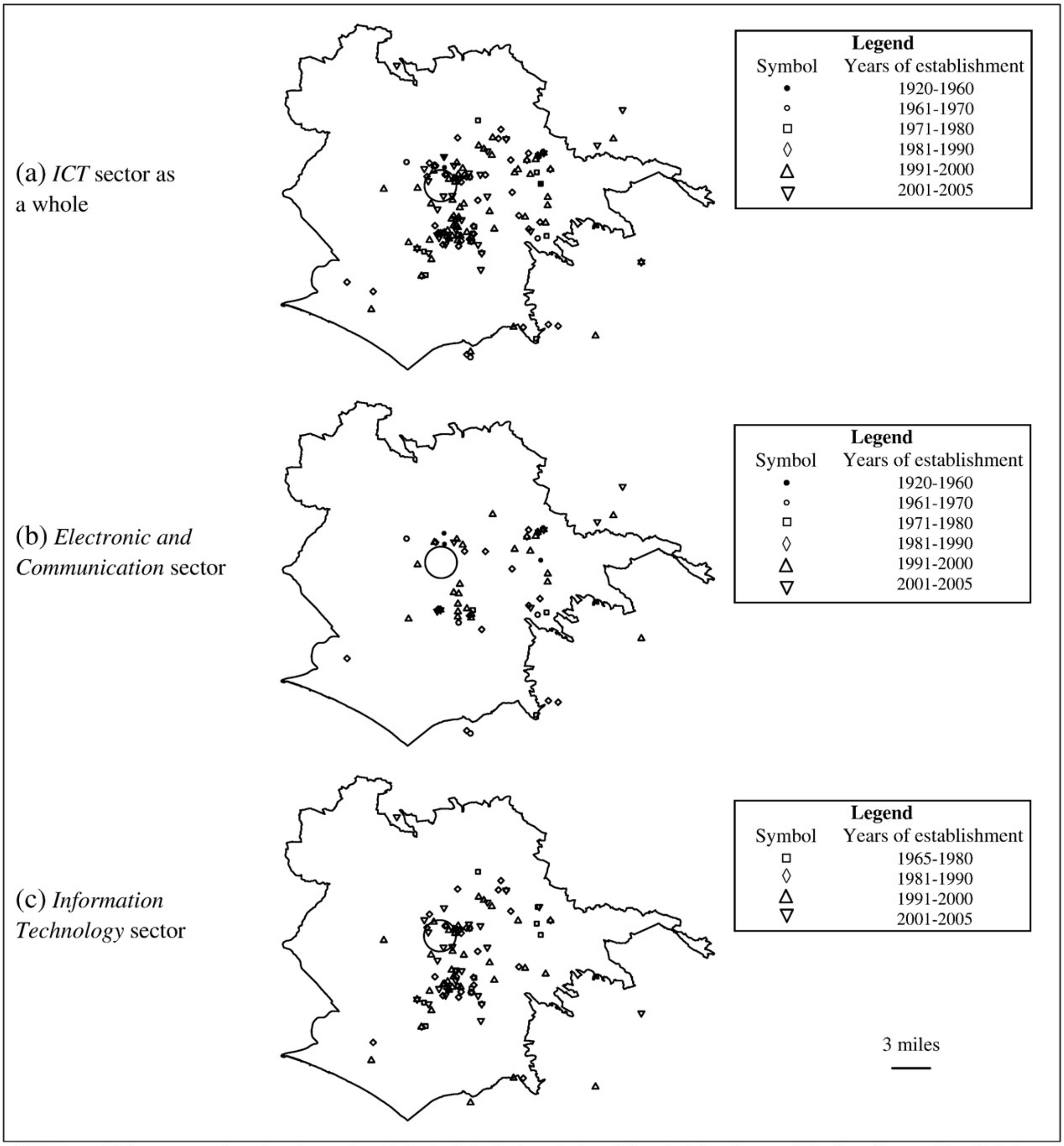
The visual inspection adds further scope to the space–time analysis that it emphasizes the interest to test whether the spatial and temporal distributions are dependent and if there is any space–time interaction. This will be accomplished in the next section.

3.3. Analysis of the K-functions

3.3.1. Analysing the distribution of the ICT sector

Fig. 3 reports the plot of the space–time *K*-functions[1] computed for the 169 firms of the entire ICT sector, as a function of both space and time. In particular, Fig. 3a reports the absolute functional $\hat{D}(d,t)$ where

[1] All the computation of the *K*-functions and the related analysis were implemented using the SPLANCS library (Rowlingson and Diggle, 1993) available in the R software.



NOTE: All figures are oriented to the north and also include the boundaries of the administrative municipality of Rome. The circle in each figure represents the location of the city centre.

Fig. 2. Spatial location and time evolution of the location of 66 firms in the ICT sector in Rome (Italy), 1920–2005.
Source: Our computations on the data provided by the UIR.

the spatial distance ranges between 0 and 9 miles (9 being one fourth of the maximum possible distance in the graph) while the temporal lag ranges between 0 and 21 (21 being one fourth of the time span of 85 years). This limitation is due to the corrections that are needed in order to minimize the distortions induced by border effects (see Haase, 1995; Goreaud and Pélissier, 1999; Arbia et al., 2008).

The examination of Fig. 3a clearly suggests the presence of space–time clustering but the extent of such phenomenon is not noticeable because the range of computed values of $\hat{D}(d,t)$ is too narrow. In order to investigate more formally this space–time effect of interdependence, we also computed the relative functionals. Fig. 3b reports the plot of $\hat{D}_o(d,t)$ (see Eq. (4)). From the graph, a peak at the short spatial distances (around the zero) and at a temporal interval of one and a second peak at a distance of approximately 1 mile and a time lag of 5 years is evident. This shows that the underlying concentration phenomenon tends to drive clusters with a small spatial magnitude (circles with radius of 1 mile) and where the firms are temporally correlated in terms of the year of establishment.

To evaluate this result more formally from an inferential point of view, a set of 999 simulations was performed, permuting at random the time 'markers' attached to every point, and thus allowing us to plot the standardized residuals against the product of the separate spatial and temporal K-functions (Fig. 4). As we mentioned in Section 2, in the case of no space–time interaction the standardized residuals are expected to have zero mean and a unitary variance. Fig. 4 cannot be attached to any substantive economic interpretation.

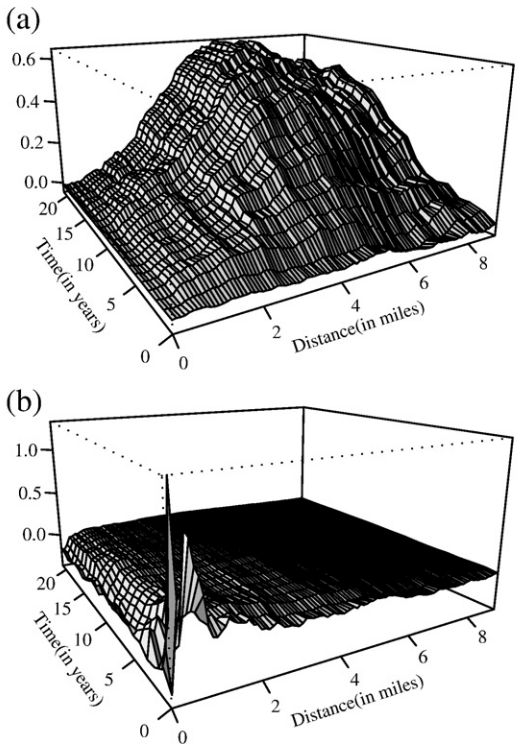


Fig. 3. 3-dimensional plot of the (a) $\hat{D}(d,t)$ function and (b) $\hat{D}_0(d,t)$ function for the ICT sector as a whole.

Indeed, it only constitutes a graphical inferential tool that can only be used to decide in favour of the presence or absence of a significant spatial structure in the observed pattern.

In the empirical case examined, we can clearly see that a relatively large number of estimated residuals lay above 2 standard errors (corresponding to 34.5% of cases) and this provides support to the hypothesis of interaction between the spatial and temporal component processes. However, because of the potentially strong interdependence among the estimates $\hat{R}(d,t)$ for different values of d and t this diagnostic plot cannot be considered particularly robust.

For this reason, in order to test the statistical significance of the results reported in Fig. 4, a Monte Carlo test of space–time clustering was performed. Fig. 5 displays the frequency distribution of the sum of the differences between the space–time K-function and the product of the separate space and time K-functions as they occurred in the 999

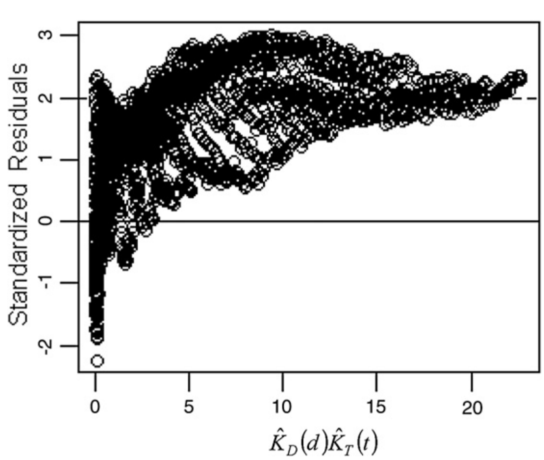


Fig. 4. Plot of the estimated standardized residuals of $\hat{R}(d,t)$ against $\hat{K}_D(d)\hat{K}_T(t)$ for the ICT sector.

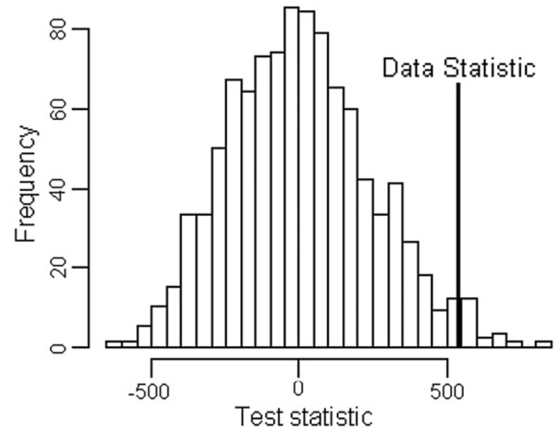


Fig. 5. Empirical frequency distribution of the sum of the differences between the space–time K-function and the product of the separate space and time K-functions in 999 simulations. ICT sector.

simulations. The sum of such differences in the observed dataset ranked 998 out of 1000. Therefore, the empirical p-value of the test is 0.002, thus providing formal evidence for the space–time clustering situation described by the plot of $\hat{D}_0(d,t)$. In other words, in the Rome area, the firms which belong to the ICT sector tend to agglomerate at a relatively small geographical distance and, moreover, the clusters are constituted by firms that established in the area with a strong dynamic component.

As already stated, the ICT sector is constituted by two groups, namely Information Technology and Electronic and Communication. In this section we wish to analyse the concentration pattern and its dynamics within the two groups separately.

Fig. 6 reports the plot of the absolute and relative D functionals for the group of firms belonging to the Information Technology industries.

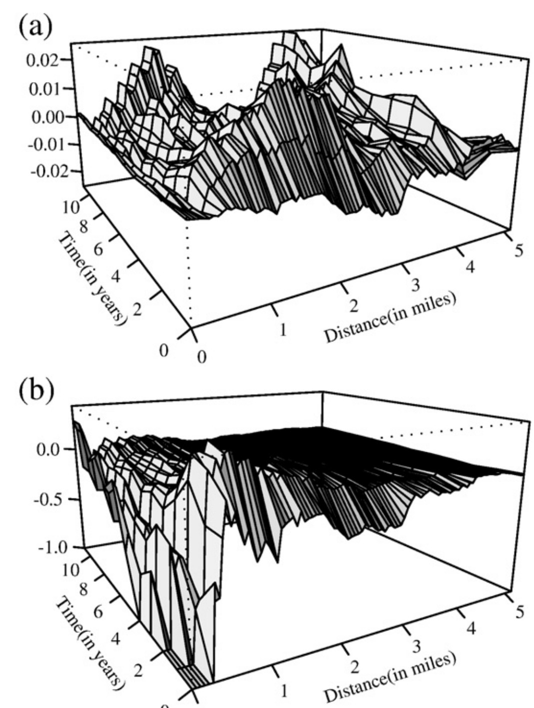


Fig. 6. 3-dimensional plot of the (a) $\hat{D}(d,t)$ function and (b) $\hat{D}_0(d,t)$ function for the Information Technology sector.

The visual features of this graph are rather different from those observed for the ICT sector as a whole (see Fig. 3). In fact, the $\hat{D}_0(d,t)$ functional displays a rather less marked spatial clustering and a negative time cluster (graph below the zero line in the time direction). More specifically, Fig. 6a displays the plot of $\hat{D}(d,t)$ where, in order to manage the edge effects, the spatial distance and the temporal lag range are respectively between 0 and 5 miles and 0 and 11 years. Although the graph shows some peaks in the surface of the functional, their magnitude is small. Indeed, the higher positive peak reaches a value of 0.025 and analogously the lower negative extremity is −0.025. As a consequence, this does not support the hypothesis of significant space–time interaction.

3.3.2. Disaggregated analysis of the two groups: "Information Technology" and "Electronic and Communication"

On the other hand, the plot of the relative functional $\hat{D}_0(d,t)$ (Fig. 6b) might suggest the presence of a weak space–time segregation phenomenon (downside peaks) within a short spatial distance and a temporal lag of approximately 4 years. These characteristics, in turn, are evidences of a tendency to locate in space and time further away from the existing firms. However, once again these visual considerations need to be supported by a more formal statistical testing procedure. In order to obtain this, we start by inspecting Fig. 7 which reports the plot of the estimated standardized residuals of $\hat{R}(d,t)$against $\hat{K}_D(d)\hat{K}_T(t)$ for the Information Technology group.

Fig. 7 shows that most of the residuals (99.5% of points) lay within the ±2 standard deviations. Thus the diagnostic test of residuals shows that the observed tendency to segregation is not substantive. Therefore the space–time segregation phenomenon, observed when commenting on Fig. 6, is not substantial and is only apparent.

This conclusion is corroborated by the Monte Carlo test for space–time interaction. To run a formal Monte Carlo test of randomness, Fig. 8 reports (as previously seen) the sum of the differences between the space–time *K*-function and the product of the separate space and time *K*-functions as they occurred in the 999 simulations. This sum in the observed dataset ranked 576 out of 1000. Therefore, the empirical *p*-value of the test is 0.424, thus providing formal evidence for the space–time randomness in the plot of $\hat{D}_0(d,t)$ and supporting the fact that the weak negative interaction between the spatial and temporal component processes occurred by chance and is not driven by a systematic underlying phenomenon. As a consequence, even if in Rome the ICT industries as a whole tend to be clustered both in space and time, those belonging to the Information Technology group present spatial agglomeration in each time period but no significant interaction between space and time. This behaviour is similar to the stylized fact presented in Fig. 1 Case v).

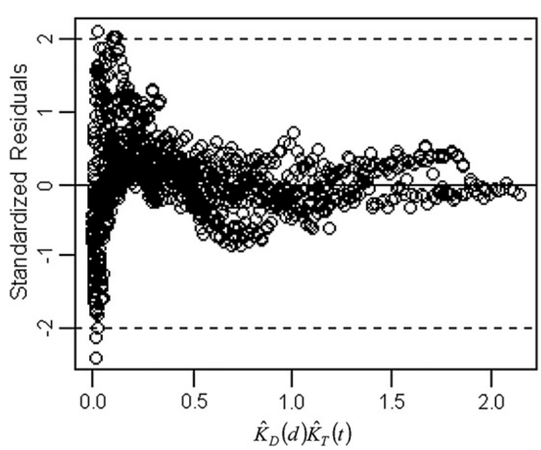


Fig. 7. Plot of the estimated standardized residuals of $\hat{R}(d,t)$ against $\hat{K}_D(d)\hat{K}_T(t)$ for the Information Technology group.

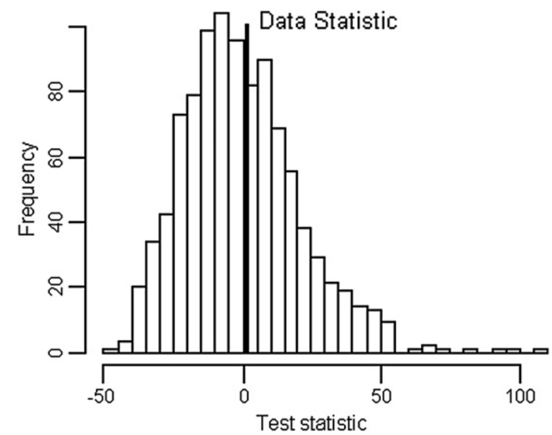


Fig. 8. Empirical frequency distribution of the sum of the differences between the space–time *K*-function and the product of the separate space and time *K*-functions in 999 simulations. Information Technology group.

Let us now move to comment on similar graphics and test for the Electronic and Communication group. Fig. 9 reports the plot of the space–time *K*-functions computed for the 66 Electronic and Communication industries observed in the area of Rome. Again, as in Fig. 3, we find evidence of a space–time clustering at short distances with a peak around zero distance and at a temporal interval of 1. The Electronic and Communication firms therefore display a similar pattern to that observed for the ICT industries considered as a whole.

Fig. 10 reports the standardized residuals originated by 999 random permutations of the industrial sites plotted against the product of the separate spatial and temporal *K*-functions. A high share of the residuals (46.5%) lies above the 2 standard deviations line thus supporting the hypothesis of dependence between the spatial and temporal component processes and the significance of the considerations made regarding the previous graph.

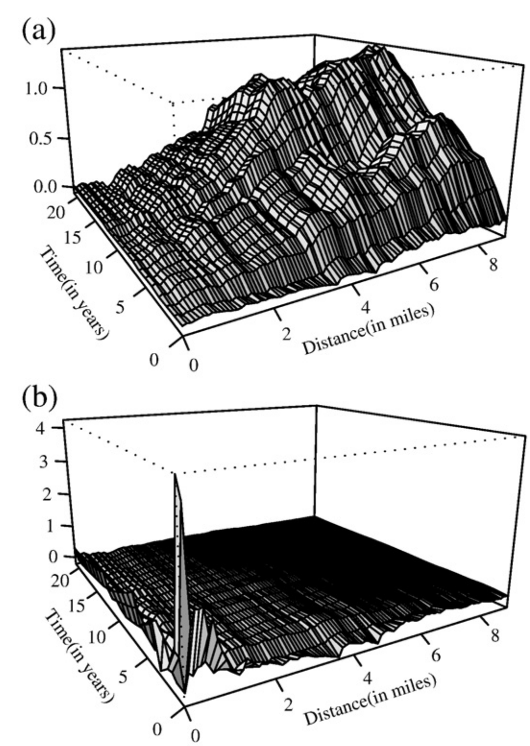


Fig. 9. 3-dimensional plot of the (a) $\hat{D}(d,t)$ function and (b) $\hat{D}_0(d,t)$ function for the Electronic and Communication group.

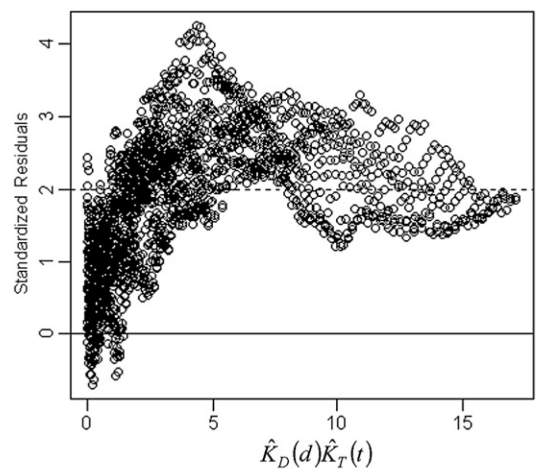


Fig. 10. Standardized residual plots of $\hat{R}(d,t)$ against $\hat{K}_D(d)\hat{K}_T(t)$ for the Electronic and Communication sector.

Finally Fig. 11 displays the frequency distribution of the sum of the differences between the space–time *K*-function and the product of the separate space and time *K*-functions in the 999 simulations. The sum of such differences in the observed dataset ranked 993 out of 1000 leading to an empirical *p*-value of 0.007 and hence providing a probabilistic significance to the previously observed space–time clustering pattern.

Summing up, the Information Technology and the Electronic and Communication groups have a different spatial behaviour. The Information Technology industries tend to locate in space with no remarkable space–time interaction. Conversely the Electronic and Communication companies tend to display a marked agglomeration pattern both in space (at small distances) and time. This dynamic effect is so strong that it is the one which dominates if we look at the ICT sector as a whole.

4. Discussion and analysis of the economic implications

The empirical findings reported in Section 3 clearly display a different spatial pattern in the distribution of firms belonging to the Information Technology and those belonging to the Electronic and Communication groups within the ICT sector. The observed clustering process for the sector as a whole is mainly due to the very strong agglomeration pattern displayed by the industries belonging to the Electronic and Communication group, while the Information Technology companies do not display any significant tendency to space–time interaction in the formation of clusters. Indeed the industries in the ICT sector are quite heterogeneous and they display different managerial and organization behaviours. The industries belonging to the Information Technology group located in our study area are mainly branches of medium–large multinational companies (the names are not reported here for privacy reasons). These enterprises make their choices in a network that is global rather than local. Thus, in their location choices they mainly tend to be present in the big metropolitan areas (basically Rome and Milan in Italy), rather than to distribute evenly over the entire territory. This global network manifests itself mainly in the form of the *global city* described by Sassen (1994) which is more aligned with the aspect of a production process than as a place in the conventional meaning: a process in which geography plays a very limited role and where the production and the consumption centres are interlinked on the basis of information flows and no longer on the basis of physical flows between the geographical space. The advent of a new high-tech manufacturing industry assisted by computers and microelectronics has led to a new logic in the localization processes. Historically the Information Technology industries were those which started this new form of spatial location based on information. Such a location pattern is characterized by the technological and managerial ability to split the production process into different places and to integrate them subsequently through computerized links (Castells, 1996). The irregular spatial distribution of activities which is thus produced was already observed empirically by, for example, Gordon (1994) who also noticed that the new distribution (determined more by information than by geography) also produced as a by-product a new spatial division of labour, characterized by *variable geometries* and by reciprocal links between industries located within spatial agglomerations (those referred to as innovation milieu; see Camagni, 1991; Castells, 1996).

With these premises one may think that in the ICT market the only driving force is what Cairncross termed the *death of distance* (see Cairncross, 2001), namely the phenomenon of a space–time compression generated by the possibility of communicating in real time with any point in the world as if everything took place in just one single dimensionless point (see also Quah, 1993). However, the realization of a production process of this kind requires direct physical interaction among entrepreneurs, managers and specialized workers in charge of integrating competences which are very different from one another.

This behaviour could be at the basis of the observed space–time clustering pattern in the Rome area for the Electronic and Communication industries and for the ICT firms as a whole despite the distribution with no space time interaction observed for the Information Technology group.

In other words the ICT industries, rather than totally eliminating the relevance of space in their location decisions, increase the need for a spatial concentration of some activities which contribute to the dispersion of other activities and are in support of the integration among them (Sassen, 1994).

In order to strengthen the idea of global networking which seems to emerge from the previous analysis, we ran a further study in which we split the data into two sub-samples: one before and one after the internet became widespread. Our theoretical expectations are that if there is less spatial clustering in the latter period, one could prove the claim of spatial location irrelevance.

The first regulation of the networking of IXPs (Internet exchange points) was introduced in Italy around 1995. From this consideration we decided to use that year as a cut-off point. We repeated our analysis separately for the two sub-samples restricting ourselves to only the ICT sector as a whole (rather than looking at Information Technology and Electronic and Communication separately) because of the small number of firms in the second sub-period. The results are summarised in Table 2 and seem to confirm our hypotheses. Indeed

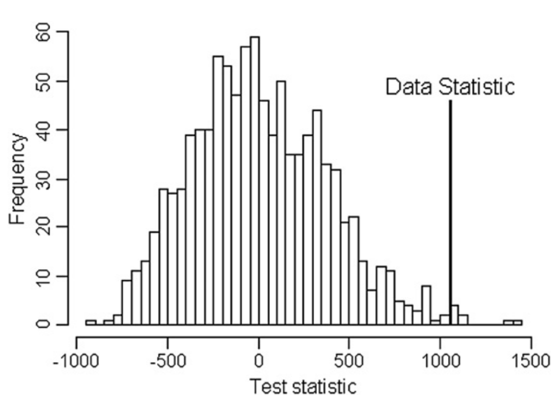


Fig. 11. Empirical frequency distribution of the sum of the differences between the space–time *K*-function and the product of the separate space and time *K*-functions in 999 simulations. Electronics and Communication group.

Table 2
Characteristics of the space–time clustering situation of the ICT sector before and after widespread internet availability.

Characteristics	Before widespread internet (before 1995)	After widespread internet
Spatial lag	1 mile	No space–time interaction
Temporal lag	1 year	–
p-value Monte Carlo test	0.011	0.592
% of estimated residuals out of ± 2 SE	40.1%	0.50%

we observe significant spatial (at 1 mile) and temporal (at 1 year) clustering in the first period (before 1995) and conversely no significant clustering either in space and time in the second one (from 1995 on).

5. Conclusions and research priorities

In this paper we have introduced a set of tools proposed in spatial statistical literature into economic literature in order to analyse simultaneously the spatial arrangements of firms, their temporal trends and the interactions between the spatial and temporal components of growth. These tools are based on the family of K-functions and fall within the realm of the so-called *marked point pattern analysis.* They were introduced, in an epidemiological context, in the seminal work of Diggle et al. (1995) and, to the best of our knowledge, this is the first time that they have been used in the regional sciences.

We argue that these tools may help the economic analysis of spatial clusters of firms by providing a proper and precise way to represent the stylized facts describing the localization processes which are to be explained by theoretical models. Moreover, they allow to empirically verify whether the time dimension is relevant in explaining the spatial arrangements of an industrial situation. Therefore, our work is not aimed at giving actual consistency to specific spatial economic models. The scientific concern in the present context is to define a way to measure the strength of the tendency for industries to cluster by taking into account the dynamic evolution of the process leading to the observed facts.

In the empirical part of this paper we have shown that the space–time K-function is an appropriate tool to uncover the process of firm demography both from a spatial and a temporal point of view and thus we are able to treat trends and cycles in time and spatial agglomeration phenomena within the same methodological framework. In particular, we have applied the proposed methodology to the space–time distribution of the ICT firms in the Rome area in the time period between 1920 and 2005.

In this respect we obtained the following substantial findings:

- ICT firms considered as a whole tend to display a marked tendency to agglomerate in space and furthermore the process of firm creation in time presents a significant space–time interaction. New firms thus tend to be created in the neighbourhood of existing ones.
- A very similar and significant pattern is detected for the subgroup constituted by only the Electronic and Communication industries.
- In contrast, the subgroup constituted by only the Information Technology firms presents a distinctive feature with respect to the whole ICT sector. While presenting a (less marked) tendency to agglomerate in space just like the Electronic and Communication, they do not display any significant space–time interaction. The process of firm creation in time thus follows a dynamic which is independent from the spatial location of existing firms.
- By splitting the time period into two samples–one before and one after the internet became widespread in 1995–we observed significant spatial (at 1 mile) and temporal (at 1 year) clustering in the first period and conversely no significant clustering either in space and time in the second period for the ICT sector as a whole. This result seems to confirm the hypothesis of spatial location irrelevance in the internet era.

While presenting the theoretical and the empirical results, in this paper we aimed at making the usefulness of the proposed methodology clear. Once the presence of a specific space–time interaction phenomenon has been detected, the researcher is in the position to model specific hypotheses concerning the geographical and dynamical configurations of economic activities. In this respect there are many possible questions which can be addressed using the proposed methodology and we plan to tackle them in future studies. We review some of them below while describing the limitations of the examples reported in the present work and, in this manner, delineating the future agenda in the field.

A first advance with respect to the work presented here is represented by the extension of the analysis to the inter-type K-function approach proposed by Lotwick and Silverman (1982) and applied in an economic context by Arbia et al. (2008). This tool enables us to detect in more detail the complex space–time processes which may occur in practice. For example, by categorizing the point process in terms of year of establishment we could test whether the phenomena of geographic segregation or aggregation between ‘old’ and ‘young’ firms occur, and hence indicate the presence of specific leader–follower patterns. In addition, we could test the co-agglomeration dynamics between different sectors.

The space–time K-functions used in the present context are built under the basic assumption of stationarity and isotropy of the underlying generating process (Diggle, 2003; Arbia, 2006). In other words, the geography of firms is considered substantially observed in a homogeneous space. This in turn implies that we do not consider the possible presence of physical or administrative limits which could introduce strong constraints in the location choices of firms. As a consequence, one of our future research priorities would consist in removing this assumption as it is often violated in an economic context. We argue that possible methods to disentangle spatial heterogeneity and spatial aggregation phenomena could be based on the integration of inhomogeneous K-functions (Baddeley et al., 2000) in a space–time perspective. This approach has been followed in Arbia et al. (2009a,b) but it neglected the time dimension. A second possible approach to tackle this problem of heterogeneity could consist in removing the potential heterogeneous sub-areas from the initial study area, thus obtaining a homogenous map. However, this solution is not entirely satisfactory because it introduces extra complexity by leading the researcher to analyse irregular polygonal surfaces rather than rectangular areas, which indeed occurred in the present context. As a consequence, the analysis should also include methods for correcting edge effects when computing space–time K-function in study areas of complex shape (see Goreaud and Pélissier, 1999).

A further limitation of the present study consists in the fact that in order to obtain a correct analysis of firm demography we should consider not only the process of the birth of new firms but also the process of the growth of the existing ones and the space–time dynamics of the firms which cease their activity in the span of period considered (see e.g. Arbia et al., 2009a,b). In the present context we did not take into account the aspects of the growth of the firm and we totally neglected the dimension of the firm (as measured, for example, by the number of employees or the value added) in our analysis. However, when studying the pattern of industrial agglomeration dimension is of paramount importance in that a pattern of increased agglomeration of firms can be equally due to a higher number of firms concentrating in the same area or, alternatively, to the firms expanding their dimension. In contrast, in the present context we considered each economic activity in space as a dimensionless point so that what we detected was the mere geographic concentration of firms and not the more general concept of industrial agglomeration as suggested for example by Duranton and Overman (2005). An important step forward in the analysis of firm clustering in space and time would be constituted by removing this strong limitation and by considering marked point patterns where the marks refer not only to different time periods (as in the present context), but also to different firm dimensions. A final point refers to the consideration of the death of the existing firms, an aspect which was also left aside in the present paper. While a correct approach to firm demography should consider jointly the process of firm creation and that of firms ceasing their activity, from the methodological point of view this adds extra complexity. This complexity occurs because the spatial pattern and the interaction between space and time should be evaluated separately in each time period and not as the resulting process at a given moment of time as we did when analysing the empirical data on the ICT firm distribution in Rome. Methodological tools should be developed in future research to overcome this further limitation.

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References

Arbia, G., 2006. Spatial Econometrics: Statistical Foundations and Applications to Regional Convergence. Springer, Berlin.
Arbia, G., Espa, G., 1996. Statistica Economica Territoriale. Cedam, Padua.
Arbia, G., Espa, G., Quah, D., 2008. A class of spatial econometric methods in the empirical analysis of clusters of firms in the space. Empirical Economics 34, 81–103.
Arbia, G., Copetti, M., Diggle, P., 2009a. Modelling individual behaviour of firms in the study of spatial concentration. In: Fratesi, U., Senn, L. (Eds.), Growth and Innovation of Competitive Regions. Springer-Verlag, Heidelberg.
Arbia, G., Espa, G., Giuliani, D., Mazzitelli, A., 2009b. Clusters of firms on an inhomogeneous economic space: the case of high-tech manufacturing industries in Milan (Italy) in 2001. Paper Presented at the 3rd World Conference of the Spatial Econometrics Association, Barcelona, 8–9 July 2009.
Baddeley, A., Møller, J., Waagepetersen, R., 2000. Non- and semi-parametric estimation of interaction in inhomogeneous point patterns. Statistica Nederlandica 54, 329–350.
Bailey, T.C., Gatrell, A.C., 1995. Interactive Spatial Data Analysis. Longman Higher Education, Harlow.
Baltagi, B., 2008. Econometric Analysis of Panel Data, 4th edition. John Wiley & Sons, Chichester.
Boots, B.N., Getis, A., 1988. Point Pattern Analysis, Sage Scientific Geography Series, Vol. 8. Sage Publications, London.
Brülhart, M., Traeger, R., 2005. An account of geographic concentration patterns in Europe. Regional Science and Urban Economics 35, 597–624.
Cairncross, F., 1997. The Death of Distance: How the Communications Revolution Will Change Our Lives. Harvard Business School Press, Cambridge, MA.
Cairncross, F., 2001. The Death of Distance 2.0; How the Communications Revolution Will Change Our Lives. Harvard Business School Press, Cambridge.
Camagni, R., 1991. Local milieu, uncertainty and innovation networks: towards a new dynamics theory of economic space. In: Camagni, R. (Ed.), Innovation Networks: Spatial Perspective. Belhaven Press, London, pp. 121–144.
Capello, R., 1999. Spatial transfer of knowledge in high technology milieux: learning versus collective processes. Regional Studies 33 (4), 353–365.
Castells, M., 1996. The Rise of the Network Society. Blackwell Publishing Ltd, Malden, MA.
Ciccone, A., Hall, R.R., 1996. Productivity and the density of economic activity. American Economic Review 86 (1), 54–70.
Cooke, P., De Laurentis, C., Tödtling, F., Trippl, M., 2007. Regional Knowledge Economies. Edward Elgar, Cheltenham, UK.
David, P., Foray, D., 2003. Economic fundamentals of the knowledge society. Policy Futures in Education 1, 20–49.
Devereux, M.P., Griffith, R., Simpson, H., 2004. The geographic distribution of production activity in the UK. Regional Science and Urban Economics 34, 533–564.
Diggle, P.J., 2003. Statistical Analysis of Spatial Point Patterns, 2nd edition. Edward Arnold, London.
Diggle, P.J., Chetwynd, A.G., Haggkvist, R., Morris, S., 1995. Second-order analysis of space–time clustering. Statistical Methods in Medical Research 4, 124–136.
Drucker, P., 1998. From capitalism to knowledge society. In: Neef, D. (Ed.), The Knowledge Economy. Butterworth, Woburn, MA.
Dumais, G., Ellison, G., Glaeser, E.L., 2002. Geographic concentration as a dynamic process. The Review of Economics and Statistics 84, 193–204.
Duranton, G., Overman, H.G., 2005. Testing for localisation using micro-geographic data. Review of Economic Studies 72, 1077–1106.
Ellison, G., Glaeser, E.L., 1997. Geographic concentration in U.S. manufacturing industries: a dartboard approach. Journal of Political Economy 105, 5, 889–5, 927 October.
Feser, E.J., Sweeney, S.H., 2000. A test for the coincident economic and spatial clustering of business enterprises. Journal of Geographic Systems 2, 349–373.
Feser, E.J., Sweeney, S.H., 2002. Spatially binding linkages in manufacturing product chains. In: McNaughton, R.B., Green, M.B. (Eds.), Global Competition and Local Networks. Ashgate, New York, pp. 111–129.
Foray, D., 2000. L'économie de la connaissance. La Découverte, Paris.
French, N.P., McCarthy, H.E., Diggle, P.J., Proudman, C.J., 2005. Clustering of equine grass sickness cases in the United Kingdom: a study considering the effect of position-dependent reporting on the space–time *K*-function. Epidemiology and Infection 133, 343–348.
Fujita, M., Krugman, P., Venables, A., 1999. The Spatial Economy: Cities, Regions, and International Trade. MIT Press, Cambridge.
Gatrell, A.C., Bailey, T.C., Diggle, P.J., Rowlingson, B.S., 1996. Spatial point pattern analysis and its application in geographical epidemiology. Transactions of the Institute of British Geographers 21, 256–274.
Getis, A., 1964. Temporal land-use pattern analysis with the use of nearest neighbor and quadrat methods. Annals of the Association of American Geographers 54, 391–399.
Getis, A., 1983. Second-order analysis of point patterns: the case of Chicago as a multi-center urban region. The Professional Geographer 35, 73–80.
Getis, A., Boots, B., 1978. Models of Spatial Processes. Cambridge University Press, Cambridge.
Glaeser, E., Kallal, H., Scheinkman, J., Schleifer, A., 1992. Growth of cities. Journal of Political Economy 100, 1126–1152.
Gordon, R., 1994. Internationalization, multinationalization, globalization: contradictory world economies and new spatial division of labour, Santa Cruz, University of California. Center for the Study of Global Transformations, working paper 94.
Goreaud, F., Pélissier, R., 1999. On explicit formulas of edge effect correction for Ripley's K function. Journal of Vegetation Science 10, 433438.
Goreaud, F., Pélissier, R., 2003. Avoiding misinterpretation of biotic interactions with the intertype K_{12} function: population independence vs. random labelling hypotheses. Journal of Vegetation Science 14, 681–692.
Haase, P., 1995. Spatial pattern analysis in ecology based on Ripley's K-function: introduction and methods of edge correction. Journal of Vegetation Science 6 (4), 575–582.
Hamilton, J.D., 1994. Time Series Analysis. Princeton University Press, Princeton.
Henderson, J.V., 2003. Marshall's scale economies. Journal of Urban Economics 53 (1), 1–28.
Henderson, V., Kuncoro, A., Turner, M., 1995. Industrial development in cities. Journal of Political Economy 103, 1067–1085.
Hirschman, A.O., 1958. The Strategy of Economic Development. Yale University Press, Clinton, MA.
Ioannides, Y.M., Overman, H.G., 2004. Spatial evolution of the US urban system. Journal of Economic Geography 4, 131–156.
Jacobs, J., 1961. The Death and Life of Great American Cities. Random House, New York.
Jaffe, A.B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced in patent citations. Quarterly Journal of Economics 108 (3), 577–598 August.
Keeble, D., Wilkinson, F., 2000. High-Technology Clusters, Networking and Collective Learning in Europe. Ashgate, Aldershot.
Krugman, P., 1991. Geography and Trade. MIT Press, Cambridge.
Lambooy, J.G., Van Oort, F.G., 2005. Agglomeration in equilibrium? In: Brakman, S., Garretsen, H. (Eds.), Location and Competition. Routledge, London, pp. 60–80.
Lotwick, H.W., Silverman, B.W., 1982. Methods for analysing spatial processes of several types of points. Journal of the Royal Statistical Society, series B 44, 406–413.
Marcon, E., Puech, F., 2003. Evaluating geographic concentration of industries using distance-based methods. Journal of Economic Geography 3 (4), 409–428.
Marshall, A., 1920. Industry and Trade. Macmillan, London.
Nonaka, I., Takeuchi, H., 1995. The Knowledge-Creating Company. Oxford University Press, Oxford.
Organisation for Economic Co-operation and Development (OECD), 1996. The Knowledge-Based Economy. OECD, Paris.
Organisation for Economic Co-operation and Development (OECD, 2001. OECD Science, Technology and Industry Scoreboard. Towards a Knowledge-Based Economy. OECD, Paris. Also available at www1.oecd.org/publications/ebook/92-2001-04-1-2987/.
Okabe, A., Yomono, H., Kitamura, M., 1995. Statistical analysis of the distribution of points on a network. Geographical Analysis 27, 152–175.
Perroux, F., 1950. Economic space: theory and applications. Quarterly Journal of Economics 64 (1), 89–104.
Polanyi, M., 1966. The Tacit Dimension. Routledge, London.
Porter, M.E., 1998. Clusters and the new economics of competitiveness. Harvard Business Review 77–90 December.
Quah, D., 1993. Empirical cross-section dynamics in economic growth. European Economic Review 37 (2/3), 426–434.
Quah D., Simpson H. (2003) Spatial cluster empirics, mimeo.
Rallet, A., Torre, A., 1999. Is geographical proximity necessary in the innovation networks in the era of global economy? GeoJournal 49 (4), 373–380.
Rauch, J.E., 1993. Productivity gains from geographic concentration of human capital: evidence from the cities. Journal of Urban Economics 43 (3), 380–400 November.
Ripley, B.D., 1976. The second-order analysis of stationary point processes. Journal of Applied Probability 13, 255–266.

Ripley, B.D., 1977. Modelling spatial patterns (with discussion). Journal of the Royal Statistical Society, B 39, 172–212.
Rowlingson, B.S., Diggle, P.J., 1993. SPLANCS: spatial point pattern analysis code in S-Plus. Computers and Geosciences 19, 627–655.
Sassen, S., 1994. Cities in a World Economy. Pine Forge Press, London.
Saxenian, A., 1994. Regional Advantage: Culture and Competition in Silicon Valley and Route 128. Harvard University Press, Cambridge, MA.
Storper, M., 1997. The Regional World: Territorial Development in a Global Economy. Guilford Press, New York.
Storper, M., 2002. Institutions of the learning economy. In: Gertler, M., Wolfe, D. (Eds.), Innovation and Social Learning: Institutional Adaption in an Era of Technological Change. Palgrave, Basingstoke.
Storper, M., Venables, A.J., 2003. Buzz: face-to-face contact and the urban economy. Journal of Economic Geography 4 (4), 351–370.
Van Oort, F.G., 2004. Urban Growth and Innovation: Analysis of spatially bounded externalities in The Netherlands. Ashgate, Aldershot.
Yamada, I., Rogerson, P.A., 2003. An empirical comparison of edge effect correction methods applied to K-function analysis. Geographical Analysis 35, 97–109.
Yeung, H.W., Coe, N., Kelly, P., 2007. Economic Geography. Introduction to Contemporary. Blackwell Publishing.