Papers Reg. Sci. 80, 411–424 (2001)

Papers in Regional Science

Modelling the geography of economic activities on a continuous space*

Giuseppe Arbia

Department of Science, University G. d'Annunzio, Pescara, Viale Pindaro, 42, 65127 Pescara, Italy (e-mail: Arbia@Sci.Unich.it)

Received: 18 May 1998 / Accepted: 12 March 2001

Abstract. In the present article we propose a spatial micro econometric approach for studying the geographical concentration of economic activities. We analyse the incentives to use this approach rather than the traditional one based on regional aggregates. As an example, we present our prototypical theoretic model – to be seen as a continuous space version of Krugman's concentration model – that includes birth, survival and growth components. We present a numerical estimation of the birth model for a set of data referring to the concentration of the manufacturing industries in the San Marino Republic.

JEL classification: C1, O0, R3

Key words: Birth-death processes, economic geography, geographical concentration, Markov fields, regional economic growth

1 Introduction

Until relatively recently, location and physical geography characteristics have been regarded as irrelevant factors in many economic theoretical studies. Most economists have behaved as if all economic agents are concentrated in one single, dimensionless point in space, and as if transportation and communication

* The comments received by the participants to two seminars given by the author at Milano-Bocconi and Genève University are gratefully acknowledged. Thanks are also due to Guido Pellegrini of Bologna University for some references, to Milena Gasperoni of the Statistical Office of San Marino Republic for providing the data used in Section 4, to Luisella Montopolino and Giovanni Lafratta of "G. d'Annunzio" University of Chieti for producing the map reported in Figure 2, and to the two anonymous referees for many precious references and suggestions that substantially improved the original paper. The partial financial contribution of MURST 60% of Chieti University and of the Italian National Research Council # 99.01511.CT10 is also gratefully acknowledged.

costs are zero. Such topics as spatial location, interaction between agents, spatial pricing, etc., have typically been left to a small group of scholars (regional economists), and considered as unimportant from a macro-dynamic point of view.

However, this scenario is rapidly changing, and the rise of the so-called "new economic geography" has radically changed many economists' perspectives. An increasing number of economists now often recognise that "physical location and geographical spill over matters more than macro factors" (Quah 1996a). Analysis of disaggregate spatial dynamics offers significant insights for analysts interested in the macro behaviour of economies.

Examples abound in the debate on the concentration of economic activity and economic integration (Krugman and Venables 1996; Arbia 2000), the literature on R&D concentration (Smulders and Van de Klundert 1995), the work on regional convergence (Barro and Sala-i-Martin 1992; Quah 1993, 1996a,b; Sala-i-Martin 1990, 1994, 1996), and on the dynamics of regional labour markets at the continental level (Decressu and Fatas 1995).

A sound statistical methodology for spatial analysis is necessary to answer the many questions posed by the new economic geography. Indeed, spatial data cannot be understood as being generated by the classical urn model; on the contrary, they are more likely to display a certain degree of dependency. In addition to this, the geographical partitions are not just divinely given, but must also be subjectively chosen in any practical circumstance.

Methods for analysing spatial (and space-time) data have already been well-developed by statisticians (Haining 1990; Cressie 1991) and econometricians (Anselin 1988; Anselin and Florax 1995; Anselin and Bera 1998). For examples of applications in economics see, among the others, Kelejian and Robinson (1993), Haining (1994), Arbia and Espa (1996), Rey and Montouri (1999) and Conley (1999).

Furthermore, the availability of statistical data at the individual agent level has increased dramatically in recent years, due to the diffusion of spatially referenced administrative records in tandem with many GIS technologies able to analyse them (Arbia 1993). Consequently, the possibility of analysing statistical data with reference to their actual location has increased enormously. The time seems to have come for a sound statistical approach to spatial economic data.

We argue strongly here in favour of a microeconomic approach to spatial analysis – as opposed to the traditional approach based on regional aggregates, which we will henceforth refer to as a mesoeconomic approach. We review in Sect. 2 some of the known inconsistencies and problems deriving from the use of mesoeconomic data and examine the advantages of using micro data to explain spatial economic behaviour. As an example of a micro-economic approach to regional problems, we introduce an explanatory model in Sect. 3. The geographical concentration of economic activities is defined in terms of the density of a non-stationary point process on a continuous space, and further on in Sect. 4 we illustrate the model with a numerical example based on real data. We provide tentative conclusions in Sect. 5.

2 Towards a continuous space approach to regional economic problems

The path-breaking lectures of Paul Krugman at Leuven University (Krugman, 1991a) stimulated interest in the so-called "new economic geography" by revealing links between the two previously unrelated fields of international economics and economic geography. Statistical evidence of the geographical concentration pattern of many industries in the US, based on the computation of Gini locational coefficients, is the basis of the Krugman model. In parallel with Krugman's model of regional concentration, we find that most of the literature on regional convergence is also based on measures of regional disparities (such as inter-regional variance, the so-called σ-convergence; see Barro and Sala-i-Martin 1992; Sala-i-Martin 1990, 1996). Since much of the literature in the field is grounded on measures of disparity between regions, before proceeding any further, we will discuss the meaning of a measure of geographical variability based on regional data.

When we measure spatial variability using regional data a number of problems arise. The first is what in statistics is known as the "Modifiable Areal Unit Problem" (henceforth referred to as the MAUP), which refers to the arbitrariness of the geographical partition used. The problem has long been recognised by statisticians who have produced abundant studies on the MAUP effects on the various statistical measures (see Gehlke and Biehl 1934; Yule and Kendall 1950; Openshaw 1981; Amrhein 1995; Wong and Amrhein, 1996). An anthology of paradoxical examples and formal results can be found in Arbia (1989).

The arbitrariness of geographical boundaries gives rise to two different manifestations, namely aggregation and scale.[1] Let us consider the examples reported in Fig. 1. Figure 1a presents an obvious situation of a strong geographic concentration at the centre of the study area. Suppose we want to measure the concentration by regional aggregates, and that we superimpose – or use a previously defined – grid of quadrats, as in Fig. 1b. In this situation any concentration measure would identify the absence of concentration. However, if we use the same grid, but we shift the origin in the northwest direction as in Fig. 1c, we would reach the opposite conclusion, since any concentration index would identify a maximum level of concentration. Herein is the description of the aggregation problem.

Conversely, if we examine the case where we superimpose a finer grid of quadrats (one-fourth the size of the previous one) onto the same set of data, a concentration index will take a value that is intermediate between case 1b and case 1c. Here is the description of the scale problem.

We can easily imagine that the situation is even worse in real cases, where the spatial units are irregular in size and shape, thus yielding an even higher degree of arbitrariness.

This example makes patent that, by observing any geographical distribution through regional aggregates, we are in fact observing two separate phenomena

[1] The term *scale* is used here in accordance with Openshaw and Taylor (1979) and Arbia (1989). The term *resolution* is sometimes used as a synonym.

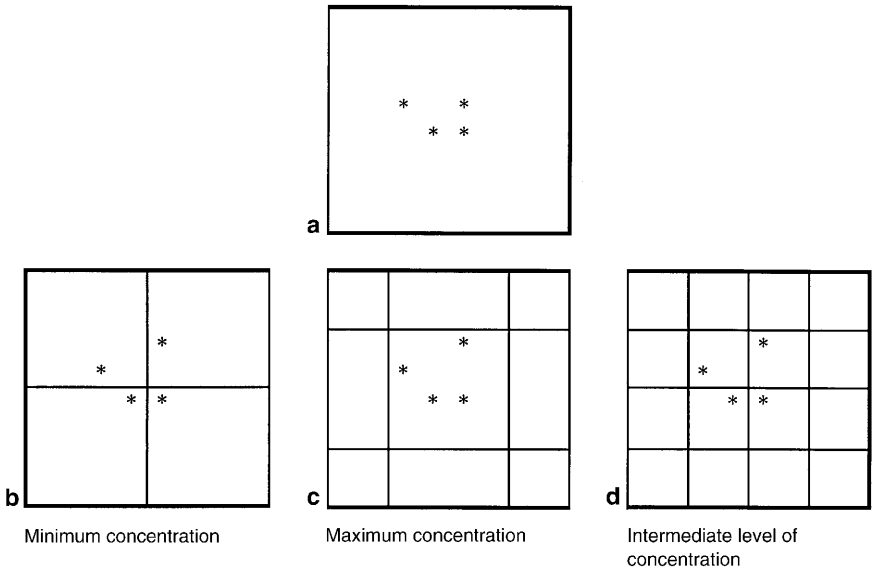

Fig. 1a–d. A continuous space distribution of firms (**a**) and three discretised versions of it. Figures (**b**) and (**c**) illustrate the *aggregation* problem. Figures (**b**) and (**d**) illustrate the *scale* problem. Each asterisk represents a firm

which are matched in an unpredictable way with regard to: i) the actual distribution of objects in the space, and ii) the partitioning considered. Thus the regional distributions are artefacts with no substantive meaning; this problem is not peculiar to spatial data and we encounter it when we aggregate time series data, (e.g., from monthly to annual), or in general when we group statistical observations into class intervals. As a matter of fact, any statistical measure based on spatial aggregates is sensitive to the scale and aggregation problems.

Arbia (1989) shows that the distortions due to scale and aggregation are minimised (but never eliminated) under some very restrictive conditions involving the identity of the sub-areas considered (in terms of size, shape and neighbouring structure), and the absence of spatial interdependence. Such conditions are never realised in economic geography – where data are observed within administrative regions that are unequal in size, shape and neighbourhood – and where, typically, neighbouring regions usually resemble each other more than regions that are far apart (the essence of Tobler's "First Law of Geography"; see Tobler 1970). Arbia (1989) in particular demonstrates analytically that by aggregating spatial units we observe a general decrease of variance and an increase of the correlation between pairs of variables (the so-called "Second Law of Geography"; see Arbia et al. 1996).

Therefore, conclusions based on β-convergence measures (Sala-i-Martin, 1990, 1996) for example, are not absolute, but are instead only relative to the particular administrative partition used; they could be very different if another

partition is used. Furthermore, any attempt to measure spatial concentration is doomed to produce non-unique results (Arbia 2000).

Why should we not simply remove the boundaries, and proceed to analyse the economy on a continuous space? Economists often see that economic activities locate on a continuous space and that "there is no particular reason to think that national boundaries define a relevant region" (Krugman 1991a,b). So why should a regional boundary define a relevant region?

We are not saying here that boundaries should be altogether ignored, but only that we need to distinguish between the meanings of boundaries in different situations. In some instances boundaries can be classified as significant borders, that is, as places where the economic conditions change abruptly because of some change for example, in the tax system, or in transport costs. In other instances we can speak of irrelevant borders, where nothing actually happens from an economic standpoint. In such instances it definitely becomes reasonable to incorporate information on significant boundaries into an explanatory model (as we shall see later). But in the meantime at this early stage of an exploratory analysis we can simply ignore both kinds of boundaries. By starting from these considerations, we think that the shift of emphasis from a meso- to a micro-level is likely to bear interesting fruit.

Krugman (1991a) has remarked that "If we want to understand differences in national growth rate, a good place to start is by examining differences in regional growth". Here we assert that a good way to understand regional economics is to begin by examining the micro behaviour of economic agents in the space economy, and so explore the micro foundations of regional economics. After a model has been identified at the micro spatial level, we can certainly superimpose an administrative grid and examine the implied meso-scenario.

In fact, phenomena in nature are encountered on a continuous space and are developed over continuous time; it is only our limitations that push us to discretise phenomena in some way (and subsequently distort it by reducing the quantity of information). Apart from the motivations given in the previous sections, a more remote incentive to study the continuous properties of economic phenomena dates back to Leibnitz and his famous quote: "Natura non facit saltus" (Leibnitz, 1703). The same general idea has been adopted in time series analysis with the development of continuous time econometrics, and is providing significant contributions to many branches of economics (on the subject, see Gandolfo 1990; Bergstrom 1990).

The idea of continuous space modelling is not new in economic geography and spatial economics; it was already present in the studies of Weber on industrial location at the beginning of the twentieth century (Weber, 1909). More recently Beckmann (1970) and Beckmann and Puu (1995) analyse equilibrium conditions of models defined on a continuous space. Griffith (1986) discusses a spatial demand curve based on a central place economic landscape defined on a continuous surface. Kaashoek and Paelinck (1994, 1996, 1998) derive the properties of a non-equilibrium dynamic path of continuous space economic variables based on partial differential equation theory (John 1978; Toda 1989). However, these

studies are all concerned with the theoretical properties of models, whereas we are interested to identify models susceptible to statistical estimation and testing on the basis of existing data.

There are many reasons why such an approach has not been adopted thus far. The most obvious are lack of an appropriate statistical methodology, lack of accurate data (often not available for confidentiality reasons), and lack of appropriate computer technologies. However, the methods for analysing spatial data on a continuous space now form a well-consolidated methodological body (Cressie 1991; Diggle 1983; Arbia and Espa 1996), even though not all the inconsistencies with the discrete counter-part have yet been removed (see Arbia 1992; Rozanov 1993; Cressie 1996). The availability of statistical data at the individual agent level has also increased considerably in recent times, due to the diffusion of spatially-referenced administrative records, and the development of methods to conceal confidential data without seriously distorting the statistical information (see Cox 1980; Duncan and Lambert 1986; De Waal and Willenborg 1994; Willenborg and De Waal 1996)

Finally, the possibility of an automated statistical analysis at surprisingly numerous levels of disaggregation has also increased dramatically due to the introduction of the modern GIS technologies.[2] Therefore, there no longer appear to be any technical obstacles in a microeconomic approach to regional problems. We will formalise such an approach in the next section.

3 A continuous space version of Krugman's concentration model

3.1 Generalities

In this section we will introduce a class of testable models to help explain the concentration of firms in space. The formalism is taken from Arbia (1996) and derives from a model proposed by Rathbun and Cressie (1994) for the spatial diffusion of vegetation. Our modelling framework also shares a particular resemblance with the methodology employed by Van Wissen (2000) to simulate the dynamics of firm demography in the space. However, even if the set-up of the model is similar, we must emphasise that in Van Wissen's approach (as in other recent works on firm demography, see Bade and Nerlinger 2000; Van Dijk and Pellenbar 2000), the aim is to model firm behaviour within regions. Our goal, however, is to explain why a firm locates (develops and dies) at a certain point in space, and thus be further enabled to tackle the MAUP and use proximity as a predictor.

Generally speaking, spatial concentration of economic activities can be due to two different reasons, which we shall keep separate in the modelling phase.

[2] As in many other fields the concern on execution time is rapidly diminishing with the introduction of new and faster processors. The execution time depends very much on the complexity of the spatial system and on the nature of the model. However for reasonably regular spatial networks estimating a model based on some hundred of thousands of spatially referenced individuals by using one of the current generation computers does not take more than few hours.

We can either have a high number of firms close to one another, or alternatively have a small number of very large firms. Under a dynamic point of view, higher concentration is realised either because new firms locate in the same area, or because the existing firms grow. The distinction obviously becomes unnecessary when we analyse data at a regional level, but it is indeed essential in our context. We will therefore model separately a *birth* process for the new firms and a *growth* process for existing firms.

3.2 A birth process

In order to introduce a birth process for the location of firms in a continuous space, let us start by defining A as the study area, $\mathbf{u} = [u_1, u_2]$ $(u_1, u_2 \in \Re)$, as the spatial co-ordinates of the firms, N as the number of firms located in A, D_i $(i = 1, \ldots, N)$ as the dimension of i-th firm (as measured by e.g., number of employees, gross product, or other), and $\delta(\mathbf{u})$ as a region in the neighbourhood of the point with co-ordinates $\mathbf{u}$.

Let us further define the local density of the process (or intensity, see Diggle 1983; Rathbun and Cressie 1994) at point $\mathbf{u}$ as:

$$\lambda(\mathbf{u}) = \lim_{\delta(\mathbf{u}) \to 0} \frac{\mathrm{E}[N(\delta(\mathbf{u}))]}{\delta(\mathbf{u})} \tag{1}$$

representing the expected number of firms in the infinitesimal area.

If the process is stationary, then $\lambda(\mathbf{u})$ will be constant in A and we can encounter three different paradigmatic situations. They are the following: a) complete spatial randomness; b) inhibition (i.e., firms are more dispersed than in the random case); and c) concentration (i.e., firms are more concentrated than in the random case; see Diggle 1983 and Arbia and Espa 1996 for examples.) The three situations are obviously far too simple to describe real cases where, for a variety of economic reasons, some places are more likely than others to host the location of firms in an irregular pattern. A good way to model such a situation is to build up a birth process for the firms in which the spatial intensity is non-stationary across the economy and varies according to location.

In specifying a model for the birth process, we can assume that the location of the firms in a past instance of time is given (thus incorporating Krugman's idea of "historical initial conditions"; see Krugman, 1991a), and the location of new firms is the realisation of a non-stationary point process (Diggle 1983).

More explicitly, we can express the intensity of the process in the point of co-ordinates $\mathbf{u}$ as:

$$\lambda(\mathbf{u}) = \exp\{\beta_0 + \beta_1 d(\mathbf{u}) + \beta_2 W(\mathbf{u}) + \boldsymbol{\beta}_3 \mathbf{X} + \boldsymbol{\beta}_4 \mathbf{R} + \Phi(\mathbf{u})\} \tag{2}$$

with $\boldsymbol{\beta} = \{\beta_0, \beta_1, \beta_2, \boldsymbol{\beta}_3, \boldsymbol{\beta}_4\}$ as a vector of parameters to be estimated. High $\lambda(\mathbf{u})$ indicate a concentration of economic activity in the infinitesimal area centred in $\mathbf{u}$. If we associate the corresponding estimated density to each point in the area we monitor spatial concentration on a continuous space. In Equation (2) $d(\mathbf{u})$ indicates the distance of point $\mathbf{u}$ from main roads, communication networks, and other significative points. This term incorporates the cost of shipping

the raw materials from the origin to the production site and the final goods from the production site to the market. $W(\mathbf{u})$ is a term measuring the sign and the intensity of the interaction between the firm located in point $\mathbf{u}$ and the other existing firms and incorporates the idea of non-constant spatial returns. A particular specification for the $W(\mathbf{u})$ function is suggested in Arbia (1996). Furthermore, in Equation (2) $\mathbf{X}$ represents a vector of independent variables assumed to be spatially heterogeneous (such as demand or unitary transport costs), and $\mathbf{R}$ represents a vector of exogenous regional policy instruments (such as local taxation, incentives) that can stimulate (or depress) the concentration of economic activities in the long-run.

Finally $\Phi(\mathbf{u})$ is the error term of the model assumed to be spatially stationary, Gaussian and zero mean, but non-zero spatial correlations. Due to the nature of the error term, the estimation of Equation (2) presents some problems that will be discussed more thoroughly in Sect. 4 when we discuss a numerical application of the model.

Equation (2) can be seen as a continuous space version of Krugman's concentration model that avoids the problems associated with arbitrary geographical partitions. The birth process can be supplemented with a death/survival process to account for dynamics. In order to introduce dynamics in the model, let us define the survivorship indicator at time t as:

$$M_i(t) = \begin{cases} 1 & \text{if the } i\text{th firm survives at time } t \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Let us also define the survival conditional probability at time $t+1$ as:

$$P_i(t+1,\theta) = \text{Prob}\{M_i(t+1,\theta) = 1 | M_i(t,\theta) = 1\} \tag{4}$$

We will assume that the survival at time $t+1$ is a function of the dimension of the firm at time t, of the competitive influence (positive or negative) with the neighbouring firms, of the global growth of the sector (nation-wide or region-wide), and of a set of explanatory variables and regional policy instruments.

When we apply the logistic transformation to the probability P_i, we can model it by using a spatial auto-logit model (Heagerty and Lele 1998) specified as:

$$\text{Logit}[P_i(t+1,\theta)] = \phi_{i0} + \phi_{i1}D_{i,t} + \phi_{i2}Y^* + \varphi_{i3}\mathbf{X} + \varphi_{i4}\mathbf{R} + \phi_{i5}\mathbf{W}_t(\mathbf{u_i}) \tag{5}$$

where, in addition to the previously introduced notation, $\varphi = \{\phi_{i0}, \phi_{i1}, \phi_{i2}, \varphi_{i3}, \varphi_{i4}, \phi_{i5}\}$ is a set of parameters to be estimated, $D_{i,t}$ the dimension of the i-th firm at time t, Y^* the global growth of the sector, and $W_t(\mathbf{u}_\text{i})$ a measure of the intensity of interaction at time t of the i-th firm with its geographical neighbours. For a specification of $W_t(\mathbf{u}_\text{i})$, see Arbia (1996). For a meso-level analogue of Equation (5), see Van Wissen (2000). Equation (5) represents a space-time auto-logistic model (Cox, 1970; Rathbun and Cressie 1994), and could be estimated using the standard Maximum Likelihood procedure.

3.3 A growth process

The birth and death/survival models account for the mere absence/presence of firms in space, but as we have mentioned above, there is a second source of spatial concentration in the growth process of existing firms.

To describe a growth process, we can divide the N_t existing firms at time t in K dimensional classes. We further define $\mathbf{u}_{ik}$ as the co-ordinates of the i-th firm belonging to the dimensional class k ($k = 1, \ldots, K$). We expand on the first m_k ($i = 1, \ldots, m_k$) firms of dimensional class k as surviving at time $(t + 1)$, and the remaining $n_k - m_k$ firms ($i = m_{k+1}, \ldots, n_k$) as ceasing their activity in the interval $(t, t + 1)$. Furthermore, let $D_{ik,t}$ be the dimension of the i-th firm belonging to the dimensional class k at time t, and let $Y_{ik,t}$ be a measure of the growth of the i-th firm belonging to the dimensional class k between time t and time $t + 1$. For instance, we can assume $Y_{ik,t} = (D_{ik,t+1} - D_{ik,t})/D_{ik,t}$, but other definitions are possible.

The proposed model describes the spatial growth $Y_{ik,t}$ as a function of the stage of development of the firm, of its exposure to external sectoral shocks, of the non-constant returns (positive or negative) deriving from being in close proximity to other existing firms, and of a set of explanatory variables.

More formally we have:

$$Y_{ik,t} = \alpha_{i0} + \alpha_{i1} D_{ik,t} + \alpha_{i2} Y^* + \boldsymbol{\alpha}_{i3}\mathbf{X} + \boldsymbol{\alpha}_{i4}\mathbf{R} + \sum_{j=1}^{K} \gamma_{ij} W_{tj}\,(\mathbf{u_{ik}}) + \varepsilon_{ik} \qquad (6)$$

where, in addition to the previous notation, $\boldsymbol{\alpha} = [\alpha_{i0}, \alpha_{i1}, \alpha_{i2}, \boldsymbol{\alpha}_{i3}, \boldsymbol{\alpha}_{i4}, \gamma_{i1}, \ldots, \gamma_{ik}]$ is a set of parameters to be estimated, $W_{jt}(\mathbf{u}_{\mathrm{ik}})$ is a measure of the intensity of interaction of firm i belonging to the dimensional class k with its geographical neighbours belonging to the dimensional class j, and the ε_{ik}'s are independently and normally distributed noises with zero mean and finite variance. Given these assumptions, the estimation of Equation (6) presents no statistical problem and can be performed by using the Ordinary Least Squares (OLS) estimators.

4 An empirical example of birth process modelling: The geographical concentration of manufacturing industries in the San Marino Republic

For illustrative purposes, we will now present an application of the birth model (2) to a set of empirical data. Our data refer to the location of manufacturing industries in the Republic of San Marino. We chose this data set for a number of reasons.

First, due to the small dimension of San Marino, data on economic activity are very rich, both in terms of the number of variables surveyed and in terms of the time frequency. In fact, complete census-type data on economic activity are updated continuously for San Marino and published yearly by the local Statistical Office. The data set contains such information on the firms as address, sector of activity, and typology of the main product. The main data set can also easily

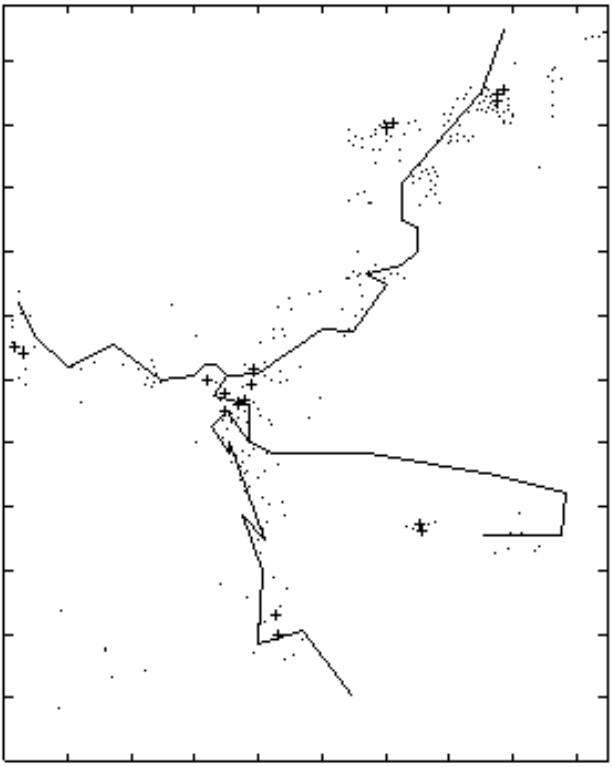

Fig. 2. Location of the 298 manufacturing industries of the San Marino Republic on 1 January 1996 (indicated by *dots*), of the 18 firms born during 1995 (indicated by the + *sign*), and path of the main roads. The map is oriented with the top to the north. The *markers* in the horizontal and vertical axes are approximately every 830 meters

be linked to other official databases containing such variables as employees, production, and many others. This richness of information is not fully exploited here, since we restrict ourselves to the birth model in the estimation process. However, they can prove invaluable in future extensions of this work.

Secondly, even if the data refer to a very small region of the world (of approximately 61.19 square kilometres), they fully describe an area that constitutes an autonomous region with its own peculiar characteristics in terms of laws, tax regulation and political institutions.

Finally, the area has a good road system and is not impeded by any physical obstacle to industrial settlements.

Figure 2 shows the location of 298 manufacturing industries present on 1 January 1996 (Statistical Office 1996). Eighteen of these firms, born in 1995, are displayed with a "+" in the same graph. Figure 2 also shows the path of the main roads that cross San Marino. There is clear evidence of agglomeration between firms, in the neighbourhood of the main roads, and in proximity of the main border with Italy (the top-right corner of the map).

In the numerical example reported here we consider a simplified version of Krugman's spatially continuous model (2), in which the intensity of the new firms depends only on the distance from the main roads, and on the interaction with previously existing firms. For the peculiarity of the San Marino Republic, it is reasonable to neglect the spatial variability of transport costs, of the demand for goods, and of regional policy measures. Hence we can express the spatial intensity of new firms, $\lambda(\mathbf{u})$, as:

$$\lambda(\mathbf{u}) = \exp\{\beta_0 + \beta_1 d(\mathbf{u}) + \beta_2 W(\mathbf{u}) + \Phi(\mathbf{u})\},$$

where $d(\mathbf{u})$ indicates the distance in meters of each point of coordinates $\mathbf{u}$ from the closest road. For the interaction term $W(\mathbf{u})$ we consider the particular specification suggested in Arbia (1996). In particular we assume:

$$W(\mathbf{u}) = \begin{cases} \sum_i \exp[-r_i(\mathbf{u})] & \text{if } r_i(\mathbf{u}) \leq 3 \text{ kilometers} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where the index $i = 1, \ldots, 280$ and $r_i(\mathbf{u})$ represents the distance between the firm of co-ordinates $\mathbf{u}$ born during 1995 and the i-th firm already existing at the beginning of the same year. Interaction is restricted to firms falling within a circle with a 3-kilometres radius. The theoretical maximum distance in the area (that is, the diagonal of the rectangular region in Fig. 2), is about 8 kilometres. The error term $\Phi(\mathbf{u})$ is initially assumed to be continuous-space stationary, Gaussian and with a zero mean. For estimation purposes it is subsequently discretised onto a regular grid of 200-by-200 squares (say $\Phi(u_{ij})$, $i = 1, \ldots, 200$; $j = 1, \ldots, 200$) and it is assumed conditionally Gaussian with $E(\Phi(u_{ij}|\text{neighbours}) = \gamma \sum_i \sum_j w_{ij} \Phi(u_{ij})$ (with $w_{ij} = 1$ if the i-th and j-th squares are neighbours in the grid and zero otherwise), and $\text{Var}(\Phi(u_{ij}|\text{neighbours})) = \tau^2$.

Because the error term is unobservable, we use the modification of the EM algorithm for our estimation (Dempster et al. 1977) – proposed by Rathbun and Cressie (1994) – using the Gibbs sampler in the E step to compute the expected value of the conditional distributions, and the Newton-Raphson algorithm to find the maximum in the M step. Both the E and M steps were run using ad hoc routines. We obtain the following model:

$$\lambda(\mathbf{u}) = \exp\left\{\underset{(0.744)}{12.02} - \underset{(0.002)}{2.602} d(\mathbf{u}) + \underset{(0.012)}{0.127} W(\mathbf{u})\right\},$$

where the figures into brackets refer to the standard errors of estimates.

The proportionality constant of the model was estimated by $\hat{\beta}_0 = 12.02$ to which we cannot attach any substantive meaning. The negative value displayed by $\hat{\beta}_1$ indicates a negative relationship between the distance from the main roads and the probability of a new location of firms. This result is in accordance with theoretical expectations, due to the ease of access and shipment of raw materials and manufacturing goods. Conversely, the positive value of $\hat{\beta}_2$ indicates a positive interaction between new firm location and the location of previously existing firms. The probability of location of new firms is therefore higher in

the neighbourhood of existing firms, thus reflecting the action of positive spatial externalities typical of many economic geographic situations (Griffith 1999). The standard deviations are generally small if compared with the absolute value of the point estimates. The accuracy of the fit of the model could only be assessed with a Monte Carlo test. We used a procedure based on the visual inspection of the empirical K function (Ripley, 1977) of the observed points contrasted with the 99% bands derived from 500 simulations of the estimated model (see Arbia and Espa 1996). At all the distances ranging from 0 to 8 kilometres (sampled any 500 meters), the empirical K function lies between the bands. We interpret this as an indication to accept the estimated model as a good description of reality.

5 Conclusions

Spatial statistical methods in economic analysis have long been comparable to the six Pirandellian characters in search of an author (Pirandello, 1921): they knew what to do, but they did not know why they had to do it. The "New Economic Geography", initiated by the seminal Krugman lectures (Krugman, 1991a), provides a theoretical framework for a spatial analysis of economic data to address issues such as regional convergence, concentration of economic activities and adjustment dynamics.

We have discussed the weaknesses of an approach based on regional data and we strongly argue in favour of an approach based on micro-economic data. We formalise a prototype spatial micro-economic model describing the birth, survival and growth of firms on a continuous surface. We illustrate our model by means of a numerical example based on the geographical distribution of manufacturing firms in the San Marino Republic. Models developed along these lines can prove to be very helpful in identify the determinants of a geographical concentration of economic activities, in the monitoring of spatial firm demography, and in the testing of effects of regional policies without incurring the problems associated with arbitrary geographical boundaries.

References

Amrhein C (1995) Searching for the elusive aggregation effect: Evidence from statistical simulations. *Environment and Planning* A 27: 105–119

Anselin L (1988) *Spatial econometrics*. Kluwer Academic Publishers, Dordrecht

Anselin L, Bera AK (1998) Spatial dependence in linear regression models with an introduction to spatial econometrics. In: Ullah A, Giles DEA (eds) *Handbook of applied economic statistics*. Marcel Dekker, New York, pp 237–290

Anselin L, Florax R (1995) *New directions in spatial econometrics*. Springer, Berlin Heidelberg New York

Arbia G (1989) *Spatial data configuration in statistical analysis of regional economic and related problems*. Kluwer Academic Publisher, Dordrecht

Arbia G (1992) Aggregation over time space and individuals in economic modelling: A generating mechanism approach. In: Gandolfo G (ed) *Continuous time econometrics*. Chapman and Hall, London

Arbia G (1993) The use of GIS in spatial statistical surveys. *International Statistical Review* 61(2): 339–359

Arbia G (1996) Modelling individual behaviour of firms in the spatial economy. *Quaderni Università Commerciale Bocconi Milano* 1(96): 1–11

Arbia G (2000) The role of spatial effects in empirical analysis of regional convergence and polarization. Proceedings of the World Regional Science Association Conference, Lugano (May). *Journal of Geographical Systems* (forthcoming)

Arbia G, Espa G (1996) *Statistica economica territoriale.* CEDAM, Padova

Arbia G, Benedetti B, Espa G (1996) Effects of the MAUP on image classification. *Geographical Systems* 3(2–3): 123–141

Bade F–J, Nerlinger EA (2000) The spatial distribution of new technology-based firms: Empirical results from West Germany. *Papers in Regional Science* 79(2): 155–176

Barro RJ, Sala-i-Martin X (1992) Convergence. *Journal of Political Economy* 100(2): 223–251

Beckmann MJ (1970) The analysis of spatial diffusion processes. *Papers of Regional Science Association* 25: 109–117

Beckmann MJ, Puu T (1985) *Spatial economics: Density, potential and flow*, North Holland, Amsterdam

Bergstrom AR (1990) *Continuous time econometric modelling.* Oxford University Press, Oxford

Conley T (1999) GMM estimation with cross-sectional dependence. *Journal of Econometrics* 92(1): 1–45

Cox LH (1970) *Analysis of binary data*. Chapman & Hall, London

Cox LH (1980) Suppression methodology and statistical disclosure control. *Journal of the American Statistical Association* 75(370): 377–385

Cressie N (1991) *Statistics for spatial data.* Wiley, New York

Cressie N (1996) Change of support and the modifiable areal unit problem. *Geographical Systems* 3(2–3): 159–180

de Waal AG, Willenborg LCRJ (1994) Minimizing the number of local suppressions in a Microdata set. Technical Report, Department of Statistical Methods. CBS, BPA no. 5997-94-M1

Decressu J, Fatas A (1995) Regional labour market dynamics in Europe. *European Economic Review* 39(9): 1627–1655

Dempster AP, Laird NM, Rubin DB (1977) Maximum likelihood for incomplete data via the EM algorithm. *Journal of the Royal Statistical Society* B 39: 1–22

Diggle PJ (1983) *Statistical analysis of spatial point patterns.* Academic Press, New York

Duncan GT, Lambert D (1986) Disclosure-limited data dissemination (with discussion). *Journal of Official Statistics* 81(393): 10–28

Gandolfo G (1990) *Continuous time econometrics*. Chapman &Hall, London

Gehlke CE, Biehl K (1934) Certain effects of grouping upon the size of the correlation coefficient in census tract material. *Journal of the American Statistical Association*, Supplement 29: 169–170

Griffith DA (1986) Central place structures using constant elasticity of consumption demand cones. Part I: the infinite plane. *Economic Geography* 62: 74–84

Griffith DA (1999) Statistical and mathematical sources of regional science theory: Map pattern analysis as an example. *Papers in Regional Science* 78: 21–45

Haining RP (1990) *Spatial data analysis in the social and environmental sciences*. Cambridge University Press, Cambridge

Haining RP (1994) Testing spatial interacting market hypothesis.*Review of Economic and Statistics* 66: 576–583

Heagerty PJ, Lele SR (1998) A composite likelihood approach to binary spatial data. *Journal of the American Statistical Association* 93(443): 1099–1111

John F (1978) *Partial differential equations*. Springer, Berlin Heidelberg New York

Kaashoek JF, Paelinck JHP (1994) On potentialized partial differential equations in theoretical spatial economics.*Chaos solitons and fractals* 4(4): 585–594

Kaashoek JF, Paelinck JHP (1996) Studying the dynamics of pre-geographical space by means of space and time-potential partial differential equations. *Geographical systems* 3: 259–277

Kaashoek JF, Paelinck JHP (1998) Potentialized partial differential equations in economic geography and spatial economics: Multiple dimension and control. *Acta applicandae mathematicae* 51: 1–23

Keleijan HH, Robinson DP (1993) A suggested method of estimation for spatial interdependent models with autocorrelated errors and an application to a country expenditure model.*Papers in regional science* 72: 297–312

Krugman P (1991a) *Geography and trade*. MIT Press, Cambridge, Mass

Krugman P (1991b). Increasing returns and economic geography. *Journal of Political Economy* 99(3): 183–199

Krugman P, Venables AJ (1996) Integration, specialization and adjustment. *European Economic Review* 40: 959–967

Leibnitz GW (1703) *Neuveaux essaies sur l'entendement humain*. Book 4, Ch. 16

Openshaw S (1981) *The modifiable areal unit problem*. Catmog n. 38, University of Leeds

Openshaw S, Taylor PJ (1979) A million or so of correlated coefficients: Three experiments on the modifiable areal unit problem. In: Wrigley N, Bennett RJ (eds) *Statistical applications in the spatial sciences*. Pion, London, pp 127–144

Pirandello L (1921) *Sei personaggi in cerca di autore*. R. Bemporad &F., Florence

Quah D (1993) Galton's fallacy and the convergence hypothesis. *Scandinavian Journal of Economics* 95(4): 427–443

Quah D (1996a) Regional convergence clusters across Europe.*European Economic Review* 40: 951–958

Quah D (1996b) Empirics for economic growth and convergence.*European Economic Review* 40(6): 1353–1357

Rathbun SL, Cressie N (1994) A space time survival point process for a longleaf pine forest in Southern Georgia. *Journal of the American Statistical Association* 89(428): 1164–1174

Rey SJ, Montouri BD (1999) US regional income convergence: A spatial econometric perspective. *Regional studies* 33(2): 143–156

Ripley BD (1977) Modelling spatial patterns. *Journal of the Royal Statistical Society* B 39: 172–212

Rozanov IA (1993) *Markov random fields.* Springer Verlag, Berlin Heidelberg New York

Sala-i-Martin X (1990) *On growth and states*. Ph.D. dissertation, Harvard University, Cambridge, Mass

Sala-i-Martin X (1994) Cross-sectional regressions and the empirics of economic growth. *European Economic Review* 38: 739–747

Sala-i-Martin X (1996) Regional cohesion: Evidence and theories of regional growth and convergence. *European Economic Review* 40(6): 1325–1352

Smulders S, Van de Klundert T (1995) Imperfect competition, concentration and growth with firm-specific R&D. *European Economic Review* 39(1): 139–160

Statistical Office (1996) *Operatori economici, liberi professionisti, enti vari*. Centro elaborazione dati e statistica, Repubblica di San Marino

Tobler W (1970) A computer movie simulating urban growth in the Detroit region. *Economic Geography*, Supplement 46: 234–240

Toda M (1989) *Nonlinear waves and solitons*. Kluwer, Dordrecht

Van Dijk J, Pellenbarg PH (2000) Firm relocation decisions in the Netherlands: An ordered logit approach. *Papers in Regional Science* 79(2): 191–219

Van Wissen L (2000) A micro-simulation model of firms: Application of concepts of the demography of the firm. *Papers in Regional Science* 79(2): 111–134

Weber A (1909) *Über den Standort der Industrien.* Tübingen

Willenborg LCRJ, de Waal T (1996) *Statistical disclosure control in practice*. Springer, Berlin Heidelberg New York

Wong D, Amrhein CG (1996) Research on the MAUP: Old wine in a new bottle or real breakthrough? *Geographical Systems* 3(2–3): 73–76

Yule U, Kendall MS (1950) *An introduction to the theory of statistics.* Charles Griffin, London