NEW EXPLANATORY MODELS FOR ANALYSING SPATIAL INNOVATION: A COMPARATIVE INVESTIGATION

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ABSTRACT

Innovation research has become an important topic in regional science analysis. Yet the modelling base of much innovation research is still feeble. This paper aims to map out the research potential of recent approaches in quantitative complexity analysis, in particular Neural Networks (NNs) analysis, from the perspective of their operational applicability in the space-economy. The urban context of European innovation processes is used as an empirical background. The paper addresses also the issue of space-time transferability of the tools employed.

The first part of the paper is devoted to a concise conceptual overview and illustration of the innovation process, which is conceived of as a self-organising system. The second part presents empirical results on innovation processes in Europe. In this framework a comparative analysis is conducted between NN models and a conventional tool often used in spatial economics studies, viz. (non)linear regression analysis. The sensitivity of the various results, – by using ‘transferability’ experiments – is also examined. The empirical experiments underline the advantages and limitations of these approaches from a methodological as well as an empirical viewpoint. They appear to offer a plausible range of values of empirical outcomes, which may highlight an acceptable degree of variation in spatial innovation processes.

1. THE SCOPE OF SPATIAL INNOVATION

The period of the 1980s and 1990s has witnessed a profound interest in innovation research. At first, we have seen much attention for technological innovations as part of a long-term cycle based on Schumpeterian views (see e.g. Kleinknecht, 1988). Later on, the interest shifted from macro-economic analyses to regional and urban economic investigations into the success conditions for new innovations (e.g. incubation theory; see e.g. Davelaar, 1991) as well as to the spatio-temporal diffusion and acceptance patterns of innovations (see e.g. Bertuglia *et al*., 1997).

The spatial component has thus increasingly gained importance in innovation research. In this context, also territorial openness, spatial factor mobility and outsourcing are playing an important role. Thus, the urban region (or the urban area in a broader setting) is increasingly regarded as the main territorial focus for creative economic development. An urban region has a knowledge base, a tight socio-economic network and a cultural support mechanism which renders it suitable as a source of Schumpeterian entrepreneurs (Amin and Thrift, 1994; Sonis, 1992). This also means that the urban region offers an effective framework for spatial competition, mainly as a result of the social embeddedness of socio-economic connectivity in the city (see Simmie, 1997).

In recent years we have also seen an overwhelming interest in the spatial organisational and managerial conditions of urban regions for successful innovative behaviour. The linkages with socio-cultural processes, institutional ramifications and public-private undertakings are increasingly coming to the fore. Against this background we have to consider also the recently emerged concepts of learning regions or self-organising regions (see also van Geenhuizen and Nijkamp, 1999, and Bertuglia *et al*., 1998).

The aim of the present paper is to identify the critical success factors of spatial innovations, based on an extensive data base on entrepreneurial innovations in a series of European cities. Particular attention will be paid to spatial innovative behaviour from the viewpoint of city size, degree of centrality and sector orientation. In this context, the potential of self-organisation of regions and cities will also be addressed.

The paper is organised as follows. The next section will offer some background reflections on self-organising strategies of cities and regions from the viewpoint of innovative behaviour. Then we address in Section 3 the methodology of an empirical analysis (in particular, regression analysis and NN analysis). In this section also the data base for our comparative analysis will be described. The results of the statistical analysis of our data are then described in Section 4, while the results of the empirical experiments related to (non)linear regression analysis and NNs are illustrated in Sections 5 and 6, respectively. Section 7 offers some concluding remarks.

2. THE SELF-ORGANISING CORE COMPETENCE OF URBAN REGIONS

Modern urban regions incorporate a body of entrepreneurial and managerial skills, which gives them a competitive advantage. Examples are research institutes, laboratories, universities, consultancy firms and so forth. This productivity augmenting structure is reinforced by the synergy created by communication, information and education networks in the city. As a result, we observe that such learning regions have the ability to organise themselves in a way which provides them also a competitive advantage in a global market.

Thus, it seems plausible that modern urban regions derive their strong innovative position largely from exploiting their core competence, viz. the efficient organisation of all relevant input, processing, production and marketing activities. The core competence has two knowledge components, viz. certified knowledge incorporated in hardware and tacit knowledge incorporated in 'humanware' (using e.g. learning – by – doing principles). Especially the 'humanware' component is responsible for the articulation of the need for spatial proximity in innovation and creates the spatial framework for organisational and learning behaviour of urban regions (see also Morgan, 1997).

It should be noticed that 'humanware' may also lead to inert and routine behaviour caused by past successes. Such a danger is, for instance, reflected in path dependency of decisions, when it is almost impossible to abandon established technologies due to an accumulation of expenses, routines or capital from previous periods. Path dependency can essentially only be coped with by so-called de-learning.

The innovative success of urban regions depends thus on a variety of creating seedbed conditions in a particular area. An important additional factor is also the dissemination potential present in an urban area. In other words, how fast and to which groups are new findings or new knowledge distributed? Again urban areas have a great potential in this respect due to their self-organising power regarding networking, transformation of knowledge, human capital management, identification of knowledge needs or consensus building using stakeholders in the region.

Knowledge, managerial and organisational networks are usually regarded as a sine qua non for effective and innovative learning strategies. Such networks may be formal or informal in nature and serve to reduce uncertainty in a business environment (see Storper, 1996).

In the light of the previous remarks, it is clear that an urban area offers a complex and dynamic array of core competences which may position these areas at a highly competitive edge. On the other hand, local cultures, geographical conditions, the urban economic composition, local management styles and local governance conditions are site-specific and may hence lead to a great variation in empirical findings (see also Nijkamp and Kangasharju, 1998). Therefore, in the sequel of this paper we will try to set up a framework for comparative analysis of innovative behaviour of firms in different sectors and in different urban regions in different European countries. By using such a contrast analysis we hope to be able to identify commonalities and contrasts in innovative behaviours of firms.

3. METHODOLOGY AND DATABASE FOR THE CASE STUDY ON EUROPEAN CITIES

3.1 Introduction

The spatial and temporal aspects of innovations are a typical example of a complex evolutionary phenomenon. Spatial and economic sciences, in recent years have shown an increasing tendency to promote new ‘universal’ concepts, such as network evolution, complexity and non-linear dynamics (see Nijkamp and Reggiani, 1998). In parallel, new models and tools originating mainly from the field of artificial intelligence, like the neuro-computing approaches, are popular for their ability to map out complex patterns with uncertain or fuzzy information. Applications of neuro-computing tools, such as neural networks (NNs) and genetic algorithms (GAs) to transport analysis have also demonstrated the promising potential of these instruments in comparison with conventional analytical models, like the well-known logit model (see, e.g., Himanen *et al.*, 1998; Reggiani *et al.*, 1998a, b, c).

Scientific researchers are nowadays successfully using logit models – and the analogous spatial interaction models – as well as regression analysis (which may – analytically – be considered to be its logarithmic form). Logit models belong to the class of discrete choice models (see, e.g., McFadden, 1974) and are playing a prominent role in spatial-economic analysis due to their underlying foundation in micro-economic theory.

However, when applying a logit or spatial interaction model, the inherent *IIA assumption* (independence of irrelevant alternatives) is often disregarded or overlooked. On the other hand, probit models, which are able to overcome the IIA limitation, are more complicated and rarely used.

In this context it is certainly useful to adopt new tools such as NNs, which, because they are based on data/image processing, apparently do not suffer from any theoretically restrictive hypothesising process. NNs also show an ‘easy’ manageability in their use and application.

Beginning with the above considerations, it seems thus worthwhile to explore the NN tool, to compare it to conventional approaches like regression and logit models, and to apply it in fields of analysis other than the transportation sector. The industrial and innovation sector, where data are often uncertain and incomplete, is therefore employed – in this paper – for an empirical analysis. The subsequent Subsection 3.2 will provide a concise overview of the methodology used (regression analysis and NN analysis); Subsection 3.3 will then present the available data base. Section 4 will next be devoted to an empirical analysis using the concept of a so-called local environment score for innovation. Section 5 and Section 6 will offer the results from a regression analysis and an NN analysis, respectively. Finally, we will conclude with some methodological considerations as well as suggestions for future research.

3.2 The methodology adopted

3.2.1 Preface

A methodology serves to develop analytical tools that are also applicable outside the domain of the actual case study, e.g. generalisation or forecasting. “*The application of a model in a context other than that in which it was originally estimated is described as model transfer*” (Koppelman and Pas, 1986, p.321). The debate on model transferability has instigated numerous empirical studies, especially on spatial behaviour in the transport sector. It is evident that the analysis of transferability measures has also become a central issue in general research areas such as spatial economics. The uncertainty on future spatial-economic events has prompted many questions on the validity of scientific references, especially since the advent of the globalisation process and within the new European economic-geographical setting.

It has also increasingly become common and necessary – in adopting new techniques and models of analysis – to focus on the joint use of different tools in order to evaluate their ability to describe the observed behaviour in the application context of a changing space-economy. To this end, we have adopted – in our case-study concerned with spatial innovation analysis – two *theoretically* different techniques:

a) regression analysis
b) neural network analysis.

These two techniques will be briefly described in the following subsections.

3.2.2 Regression analysis

Regression analysis may be regarded as the conventional ‘centerpiece’ of quantitative spatial economic analysis. From a methodological viewpoint, regression analysis is also closely connected with spatial interaction modelling from both a static and dynamic perspective (see Nijkamp and Reggiani, 1992). The limitation inherent in the use of the regression model is mostly its inability to map *complex* patterns of the performance/behaviour of actors regarding the variables at hand. In general and briefly stated, regression analysis aims to correlate variables in a (non)linear, causal way as follows:

$$Z_j = f(a_i, X_i) \quad i=1\ldots n; \quad j=1\ldots m \tag{1}$$

where Z_j are dependent variables, X_i independent variables, a_i the parameters/coefficients to be estimated, and $f(.)$ the causal or explanatory relationship (which may be linear or non-linear). It should be noted that the non-linearity incorporated in (1) may be of any form, e.g. quadratic or cubic.

3.2.3 The neural network approach

NNs belong to the methodological class of biocomputing (as do genetic algorithms, fuzzy logic, cellular automata, etc.). “*Biocomputing refers to biologically inspired approaches to creating software*” (see Valdes, 1991). The idea behind biocomputing is to explain complex phenomena by means of simple rules, according to the principle that intricate structures such as living systems are comprised of simpler components (cells). Progressing both from the need to emulate the human learning process – which is based on experience – and from the concept of biocomputing, neural networks represent a new technology for information processing based on current theories concerning the way the human brain works. In a human brain, nerve cells called neurons are the fundamental elements of the central nervous system. The central nervous system has about five billion neurons; their simple cooperation generates complex behaviour. The basic features of a neuron may be summarised as follows (see Davalo and Naim, 1991):

- it receives signals coming from other neurons;
- it integrates these signals;
- it propagates the resulting signal to other neurons (with different intensities) by means of electrochemical connections.

Thus by analogy, the structure of NNs is comparable to the architecture of the human brain and is generally represented by logical units ('neurons') connected by channels of communication which intercompute independently, since each unit cooperates in the transmission of information by means of a different weight[1]. By changing the values of the weights to obtain the desired output, the learning process occurs; NNs are trained to output the desired results. The back-propagation algorithm is especially able to 'assign back' the mean-squared error signal from the output to the input units. In this way NNs can learn from experience; this is the key advantage of NNs over conventional algorithms.

The application areas of NNs are wide-ranging, although their main task is pattern recognition. In recent years, NNs have been adopted for image processing, speech synthesis, noise filtering, robotic control, financial modelling, and so on.

The term 'neural networks' is used nowadays to describe a number of different models which are usually categorised into two classes; NNs *without* and NNs *with* supervisor. This difference is based on the difference in the learning process. In fact, the networks with *unsupervised training* do not require the target outputs; they modify the weights by means of competitive learning algorithms in response to the input data. On the other hand, *supervised training* indicates the knowledge of input/output data in order to find, during the learning phase, the weights[2] of the network which minimise the error function of the target outputs and the network outputs. Although various training algorithms[3] exist, the one most often used is the back-propagation algorithm, where in the case of a two-layer feedforward NN, at least one 'hidden' layer is defined between the input and output layers to map internal representations necessary for associating input and output configurations (see Figure 3.1 and, for details on NNs, Chapter 7 in Nijkamp and Reggiani, 1998). Following the majority of applications on NNs, in this study we adopt a two-layer feedforward, totally connected NN application (see Figure 3.1). The methodological structure of the primary steps in the application of a feedforward NN is described in Reggiani and Tritapepe (1997). It consists of three subsequent stages: a) definition of network architecture; b) a learning phase; and c) a forecasting phase. It is necessary to define the correct architecture of the network, i.e. the number of units on the relevant levels. The input and output units usually depend on the number of input and output variables defining the problem.

[1] Here a weight is a real number assigned to a connection between two units.

[2] The weights are the values (adaptive coefficients) assigned to the links between the units of the network. The goal of the training phase is to find the values of the weights which will produce a reasonable output in response to the input.

[3] The aim of the training algorithm is to minimize the error function by adjusting the value of the weights.

Section 5 will offer empirical results obtained by applying a NN model to innovation data. It should be noted that the use of the NN model in the context of industrial innovation dynamics is rather rare and still in an experimental stage.

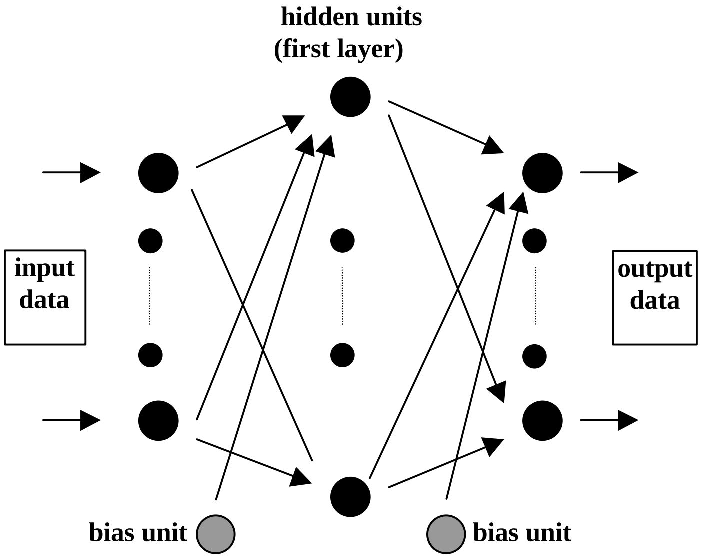

Figure 3.1. A feedforward (back-propagation) neural network architecture

3.3 The data set

The data set used in our empirical applications contains detailed information on entrepreneurial innovation based on interviews – from the URBINNO[4] study (see, for details, Damman, 1994) – of different manufacturing industries (273) in various cities in three European countries: the Netherlands (33), Italy (32) and the United Kingdom (208) (see Table 3.1).

[4] The URBINNO (Urban Innovation) study was a project originally financed by Volkswagen Foundation (between 1987 and 1989) for studying innovations in several urban areas under various categories such as population, urban economy, institution and infrastructure, and urban firm (see, for details, Damman, 1994).

Table 3.1. The geographical location of the firms under analysis

Country	The Netherlands (NL)	Italy (IT)	United Kingdom (UK)
City	Rotterdam, Eindhoven and Tilburg	Milan and Como	Sheffield, Bristol, Coventry, Newcastle Nottingham, Blackburn, Peterborough and Reading
Number of firms	33	32	208

In addition, the cities in our survey have been divided into core, intermediate and peripheral regions on – the basis of geographical location and size – in order to study the innovation adoption phenomena, not only according to their national average patterns, but also according to additional characteristics such as the size of the cities (see Table 3.2).

Table 3.2. The characteristics of the cities under consideration

	Intermediate Region	**Core Region**	**Peripheral Region**
Population	300,000-386,000	426,000-2,000,000	50,000-141,000
City	Eindhoven, Coventry, Newcastle, Nottingham	Milan, Rotterdam, Sheffield and Bristol	Blackburn, Como, Peterborough, Reading and Tilburg
Number of firms	99	93	81

According to Kangasharju and Nijkamp (1997), this implies that we expect "*the spatial diffusion to emerge not only according to physical distance to central regions, but rather according to their ability and willingness to adopt innovations (approximated here by size of a city)*" (p.10).

The extensive questionnaire submitted to the companies refers to retrospective (past) and prospective (future) views of managers on various local factors (see Table 4.1) (see, next section as well as Nijkamp *et al.*, 1997).

The next sections will depict the statistical results emerging from our empirical analysis of the interviews. These empirical experiments have been primarily based on the modelling techniques and methodologies described in Subsection 3.2.

4. ATTITUDINAL PREFERENCES OF FIRMS TOWARDS THEIR LOCAL ENVIRONMENT

For each firm a simple statistical indicator, coined the local environment score (LES[5]), has been computed in order to create a measure concerning the perception (by the firm) of the importance of the relevant local factors. Table 4.1 lists the twenty-one local factors considered in our survey.

Agglomeration	Population Structure	Information Network Infrastructure	Physical Network Infrastructure	Institutional Network Infrastructure
A1 Local suppliers **A2** Local subcontractors Quality of local business services: **A3** Supporting technology **A4** Supporting marketing **A5** Supporting management	**B1** Skills in labour market **B2** Skills in training support **B3** Local customers	**C1** Science & technology links with local university or college **C2** Management links with local university or college **C3** Chambers of commerce and industry **C4** Trade association **C5** Clubs and societies **C6** Conferences services	**D1** Quality of telecommunications services **D2** Quality of local transport facilities **D3** Quality of international transport links	**E1** Local investment subsidies **E2** Local financial institution **E3** Favourable attitude of local politicians **E4** Available land and building

Table 4.1. The twenty-one factors important to the success of the company in business, product innovation, market innovation, process innovation, and management structure (based on Kangasharju and Nijkamp, 1997).

More specifically, the importance of the local factors under analysis – perceived by each firm – has been evaluated for the following five objectives:

[5] According to Nijkamp *et al.* (1997), the local environment score (LES) is computed as follows:

$$LES = \frac{b_i * X_i + b_j * X_j}{\sum Y} * 100$$

where b_i ='major importance', b_j ='some importance', X_i = the frequency of the answers offering the score 'major importance', X_j = the frequency of the answers offering the score 'importance' and SY= the total number of possible attributes/ alternatives y. In our specific case b_i=1, b_j=2, SY=21.

a) **commercial success of the company** in the recent past as well as in the mid-1990s (future);

b) **product innovation** in the recent past and product innovation in the next decade (future);

c) **market innovation** in the recent past and market innovation in the next decade (future);

d) **production process innovation** in the recent past and production process changes in the next decade (future);

e) **management structure** or **procedural innovation** in the recent past and managerial changes in the next decade (future).

The LES indicators at the firm level have then been aggregated at the country level (see Table 4.2). The aggregate value, computed as the average of the LES scores located in each country under analysis (NL, IT, UK), offers a standard measure of the perceptions – of the firms – on the importance of the local factors, seen from their national perspective. Table 4.2 shows that the Italian firms in particular are more 'sensitive' to the importance of these local factors in comparison with the firms located in the Netherlands and the United Kingdom, which appear to be more homogeneous in their behavioural patterns. This result will most likely have a significant impact on the sensitivity analysis concerning the 'space-transferability' of the firms (see Subsection 5.3).

Table 4.2. The LES indicators in the past for the firms under analysis (country level)

Country	**Success in business**	**Product innovation**	**Market innovation**	**Process innovation**	**Management structure**
	Past	Past	Past	Past	Past
NL	61.76	24.24	13.71	14.86	4.47
IT	**101.34**	**60.71**	**56.10**	**43.00**	**43.45**
UK	76.90	20.40	23.83	17.76	17.81

The above LES indicators have also been computed for the future (see Table 4.3).

Table 4.3. The LES indicators in the future for the firms under analysis (country level)

Country	**Success in business**	**Product innovation**	**Market innovation**	**Process innovation**	**Management innovation**
	Future	Future	Future	Future	Future
NL	66.67	25.97	15.44	20.78	5.19
IT	**120.98**	**83.93**	**65.62**	**59.97**	**59.67**
UK	83.13	23.26	25.75	19.73	19.60

Table 4.3 displays the result that the perceptions about the importance of the twenty-one local factors of the Italian firms for objectives *a, b, c, d* and *e* (in Table 4.1) are higher compared to the other countries in the future context. In order to better illustrate this, we have also extrapolated the difference between the LES indicators in the future and in the past to offer a ‘dynamic’ perspective of the changes of the firms’ opinions (see Table 4.4). The positive ‘dynamic’ perception – towards the local factors – of the Italian firms compared to the Dutch and English firms, is again evident here. However, it should be noted that in general each country perceives the twenty-one local factors more important in the near future than in the past.

Table 4.4. The differences - between future and past - in the attitudinal preferences of the firms towards the adopted local factors (country level)

Country	**Success in business**	**Product innovation**	**Market innovation**	**Process innovation**	**Management innovation**
	Future-Past	Future-Past	Future-Past	Future-Past	Future-Past
NL	4.90	1.73	1.73	0.92	0.72
IT	**19.64**	**23.21**	**9.52**	**16.96**	**16.22**
UK	6.23	2.86	1.92	1.97	1.79

Our analysis will now attempt to further explore – through using the statistical-methodological tools of regression and NN analysis – the ‘behavioural attitude’ of these different clusters of firms (NL, IT, UK), in order to provide proper insight into their ‘space- transferability’ pattern.

5. AN EXPLANATORY REGRESSION ANALYSIS FOR THE LOCAL ENVIRONMENT SCORES

In this section will investigate the possibility of explaining the LES indicators relevant to the commercial *success of the company* as a (non)linear combination of the LES indicators related to *product innovation*, *market innovation*, *process innovation* and *management structure*. The methodology adopted in this section based on a simple regression model. A linear regression model will first be carried out to assess whether the variables under analysis are combined in a ‘linear’ form or are otherwise of a non-linear form, e.g., of a quadratic or cubic type. In the next section, an NN approach will be used to explore the possibility of a more complex non-linear relationship. Moreover, the NN model is also adopted as a specific tool for analysing the (micro) behaviour of the firms.

The statistical indicators ARV (Average Relative Variance), MSE (Mean Square Error), MPE (Mean Percentage Error) and MAPE (Mean Absolute Percentage Error) (see footnote 8 for their mathematical definition) are considered in this paper for the comparison and evaluation of the results for each adopted model. For this purpose the data set has been randomly subdivided into three sub-sets[6]:

- *training set* containing 218 observations, about 80% of the data set;
- *cross-validation set* containing 44 observations, about 20% of the training set;
- *test set* containing 55 observations, about 20% of the data set.

Finally, a sensitivity analysis will be carried out to analyse the 'transferability' potential (see for details Subsection 6.3), as specified at the end of Section 4.

The regression analysis concerning the LES indicators that we use here considers as a dependent variable the **LES** indicator related to the **commercial success** of the company. The independent explanatory variables are defined as follows:

Product (LES) = Local environment score related to product innovation;
Market (LES) = Local environment score related to market innovation;
Process (LES) = Local environment score related to production process innovation;
Management (LES) = Local environment score related to management performance;
Dum1_NL = Dummy variable related to a location in the Netherlands;
Dum2_IT = Dummy variable related to a location in Italy;
Dum3_UK = Dummy variable related to a location in United Kingdom;
Dum4_Peri = Dummy variable related to a location in a peripheral region;
Dum5_Cent = Dummy variable related to a location in a core region;
Dum6_Iter = Dummy variable related to a location in an intermediate region.

The data on these variables stem from the survey among the firms concerned.

Table 5.1 displays the results of the estimated coefficients for the case of a linear regression model as well as the values of the statistical confidence indicators (t-values).

[6] The training set has been used for the learning/calibration phase. The cross-validation has been used for solving the overfitting problem of a NN in the learning phase (see for details, Fischer and Gopal, 1994). The test set is used for comparing the results of the models adopted after the introduction of the data not used in the learning/calibration phase.

Table 5.1. The results of the linear regression model

Variable[7]	Coefficients	t-Value
(Constant)	98.876	14.519
Product (LES)	6.8E-02	.901
Market (LES)	.159	2.222
Process (LES)	3.8E-03	0.047
Management (LES)	-5.1E-04	-.007
Dum1_NL	-37.702	-4.407
Dum3_UK	-20.773	-3.132
Dum4_Peri	-18.014	-3.506
Dum6_Iter	-3.783	-.785

Next, we have also calculated other statistical indicators in order to allow for a comparison of the results with those stemming from NN experiments.

Table 5.2 below shows the values of these statistical indicators[8], viz. ARV, MSE, MPE and MAPE, for the above linear regression model. However, these results highlight also a possible situation of a 'hybrid solution'. In other words, we cannot confirm – from the value of the statistical indicators expressed in Table 5.2 – whether the adopted relationship among the LES indicators has a linear or non-linear specification.

[7] The dummies related to Italy and to a central location have been excluded, since they are redundant. It means that they can be expressed as a combination of the others.

[8] The Average Relative Variance (ARV) is defined as:

$$ARV = \frac{\sum (y-\hat{y})^2}{\sum (y-\bar{y})^2}\,.$$

The Mean Squared Error (MSE) is defined as:

$$MSE = \frac{1}{n}\sum (y-\hat{y})^2\,.$$

The Mean Percentage Error (MPE) is defined as:

$$MPE = \frac{1}{n}\sum \frac{\hat{y}-y}{y} * 100\,.$$

The Mean Absolute Percentage Error (MAPE) is defined as:

$$MAPE = \frac{1}{n}\sum \frac{|\hat{y}-y|}{y} * 100\,.$$

where y = the observed/target value, $\hat{y}$ = the predicted value by the adopted model, $\bar{y}$ = the average of the observed/target values and n = the number of the patterns. These indicators imply a good performance of the calibrated model, when their values are approaching zero.

Table 5.2. The values of the statistical indicators for the linear regression model

LINEAR REGRESSION MODEL				
Indicator	**ARV**	**MSE**	**MPE**	**MAPE**
Calibration set	0.788	769.59	24.49 %	45.03 %
Test set	**0.801**	**694.45**	**11.93 %**	**30.26 %**
Data set	0.799	614.55	21.96 %	42.05 %

A next step in our analysis may then be a switch to a non-linear regression by adding, for example, quadratic and cubic terms for the independent variables in the previous regression. The estimation of both these two non-linear models shows better results (see Tables 5.3 and 5.4, respectively), as they exhibit a clear non-linear pattern among the variables under scrutiny.

Table 5.3. The values of the statistical indicators for a non-linear regression model (quadratic terms for the independent variables)

NON-LINEAR REGRESSION MODEL (Quadratic terms)				
Indicator	**ARV**	**MSE**	**MPE**	**MAPE**
Calibration set	0.775	766.34	23.76 %	44.07 %
Test set	**0.798**	**679.49**	**10.79 %**	**29.55 %**
Data set	0.778	611.94	21.14 %	41.15 %

Table 5.4. The values of the statistical indicators for a non-linear regression model (quadratic and cubic terms for the independent variables)

NON-LINEAR REGRESSION MODEL (Quadratic and cubic terms)				
Indicator	**ARV**	**MSE**	**MPE**	**MAPE**
Calibration set	0.734	736.01	22.14 %	41.93 %
Test set	**0.737**	**672.03**	**11.37 %**	**30.42 %**
Data set	0.733	587.73	19.97 %	39.61%

We notice here that because a linear regression model is a logarithmic expression of a spatial interaction model, the independent variables listed in Table 5.1 can also be interpreted as utility or cost functions for the dependent variable. Seen from this perspective, our results suggest that the product innovation and market innovation indicators are more significant than the production process innovation and the management performance of the company. This finding also confirms the outcomes of a previous analysis of these data (see Kangasharju and Nijkamp, 1997).

In order to explore more thoroughly this (non-linear) explanatory relationship, we will also utilise the NN approach, which can in principle incorporate a more ‘complex’ relationships among our variables. We will describe the results emerging from the NN approach in the next section.

6. THE NEURAL NETWORK APPROACH

6.1 Neural Network results

For the experiments conducted by means of the NN approach, we have concentrated on the most popular class of NN, the two-layer feedforward totally connected, a back-propagation (BP) algorithm in order to identify the ‘optimal’ connection of the weights in the learning phase (see, for details, Subsection 3.2.3).

In our application the NN architecture contains ten inputs which correspond to the independent variables (see the previous subsection), one output unit – corresponding to the LES indicators related to the commercial success of the company (dependent variable) – and nine hidden units[9]. Figure 6.1 shows the structure of the NN model adopted in our application, while Table 6.1 displays the results after the learning phase of the NN model.

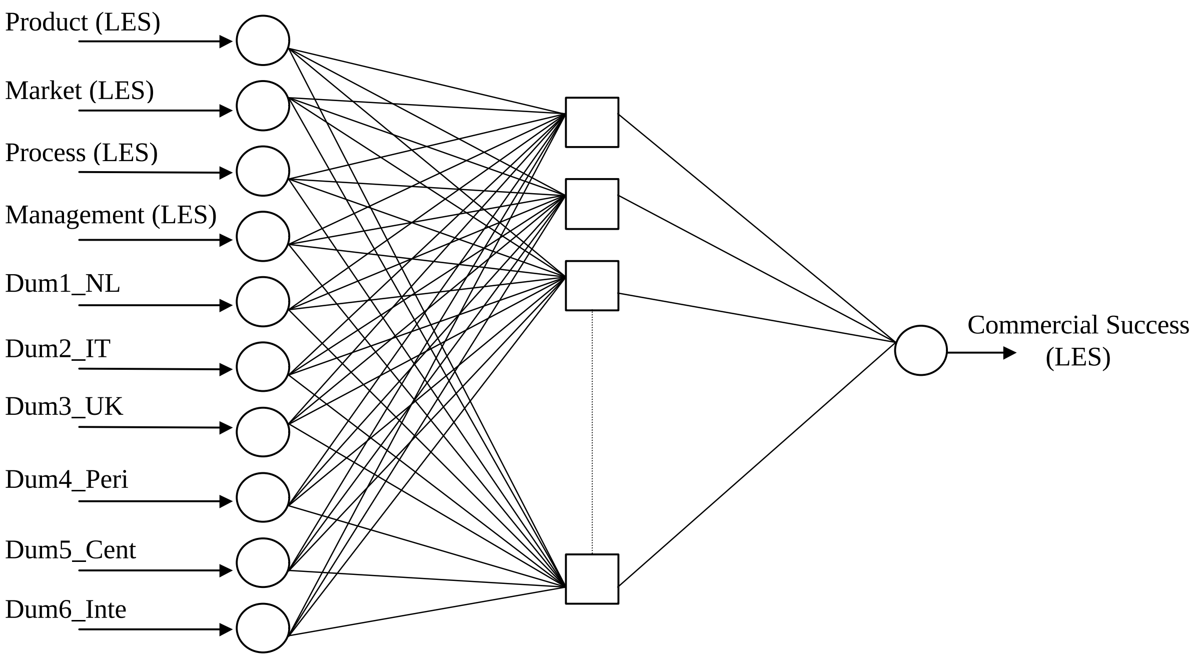

Figure 6.1. The structure of the adopted NN model

[9] The number of hidden units has been defined by a trial and error procedure.

Table 6.1. The values of statistical indicators for the NN model

NEURAL NETWORK MODEL				
Indicator	**ARV**	**MSE**	**MPE**	**MAPE**
Calibration set	0.684	685.25	20.41 %	40.33 %
Test set	**0.714**	**656.96**	**4.63 %**	**27. 63 %**
Data set	0.689	547.20	17.23 %	37.77 %

6.2 Comparison of results

The NN results show clearly a better performance of NNs compared to the previous regression models. We will now compare in more detail the NN results with those from linear, quadratic and cubic regression. The results of the test phase through the use of the regression and NN models are illustrated more specifically in Table 6.2.

Table 6.2. The results of the test phase for the adopted models

MODEL	**ARV**	**MSE**	**MPE**	**MAPE**
Linear Regression	0.801	694.45	11.93 %	30.26 %
Quadratic Regression	0.798	679.49	10.79 %	29.55 %
Quadratic + Cubic Regression	0.737	672.03	11.37 %	30.42 %
Neural Network	0.714	656.96	4.63 %	27.63 %

By examining the tables shown above we can infer that for all test statistics NN model performs much better than the three types of regression models. Consequently, we may argue that the NN analysis is able to encapsulate more complex relationships – compared to non-linear quadratic and cubic forms – among the explanatory variables at hand. Clearly, some caution is warranted here, as the statistical indicator values suggest still some potential good performance of the regression models.

6.3 Sensitivity analysis

In this section a sensitivity analysis will be carried out to analyse the space transferability issue for the firms under analysis. In other words, we will investigate the impact of the geographical allocation (NL, IT, UK) on the success of the individual firms. For this purpose, the linear and cubic regression model and the neural network model will again be utilised by varying the values of the dummy variables related to the country location (Dum1_NL, Dum2_IT and Dum3_UK). Tables 6.3 and 6.4 illustrate the results of the sensitivity analysis as an average of the results at a micro (firm) level. More precisely, Table 6.3 displays the results concerning the regression approach, while Table 6.4 shows the values for the NN approach. The micro level results for the NN model are extrapolated and illustrated in Annex A (see Tables A.1-A.3). It should be noted that, given results of the sensitivity analysis, the behaviour of the firms is comparable among all three models utilised, although the values emerging from the linear regression seem to be closer to those emerging from the NN model than the results obtained from the cubic regression. It should be note that the NN model offers the possibility of analysing the behaviour of the firm at the micro level (cf. Tables A1-A3).

Table 6.3. The results of the sensitivity analysis related to the LES variations for the variable 'commercial success' for the regression model[10]

Country	The Netherlands	Italy	United Kingdom
The Netherlands	*****	37.702 (28.125)	16.929 (9.748)
Italy	-37.702 (-28.125)	*****	-20.773 (-18.377)
United Kingdom	-16.929 (-9.748)	20.773 (18.377)	*****

Table 6.4. The results of the sensitivity analysis for the NN model

Country	The Netherlands	Italy	United Kingdom
The Netherlands	*****	49.93	13.71
Italy	-31.97	*****	-20.13
United Kingdom	-16.68	32.87	*****

In substantive terms, the information in these tables indicates that the 'Italian attitudinal preference' has apparently a positive impact, when we also include in the Italian analysis the relative position of industries from other countries, as these results show increasing positive values of LES variations. This is a plausible result, because the Italian firms revealed relatively high LES values (see Tables 4.2-4.4). On the contrary, The Netherlands demonstrates a negative variation of the LES values, in the 'hypothetical case' the Dutch/English industries would virtually 'move' to Holland. It should be noted that the UK 'behaves' in a way similar to the Netherlands. We may thus conclude this part by emphasising that the emerging behavioural pattern for the industries analysed might also offer new insights into the plausible allocation of 'new' industries.

7. SUMMARY AND CONCLUSIONS

The primary objective of this study was to analyse the self-organising mechanism of industrial innovation processes in the light of the 'new' economic and information society. Based on European data obtained from the 'URBINNO' project, our approach has followed two related sub-objectives:

a) to depict trends and dynamics of the innovation process at hand (time transferability);
b) to draw lessons from the spatial 'forecasting' of innovative industries (space transferability).

For the above purposes this study has developed a new modelling framework consisting of the joint use of a (non)linear regression model and a neural network approach.

The estimation results provide a solid argument in favour of the use of the NN model; however, both the regression and NN approach do not yet provide a sufficiently strong enough basis for choosing either model structure.

Further research should be undertaken to offer a proper methodological and practical interpretation of the available data. Within this context one research direction is surely oriented towards a further exploration of neurocomputing approaches (e.g., by investigating and employing the genetic algorithm tool in conjunction with the NN approach). Another research direction could be the use of a probit model (instead of a regression analysis), as this model is able to overcome the limitations caused by the IIA assumption.

[10] The values in parentheses denote the results for the cubic regression.

ACKNOWLEDGMENTS

This paper has been carried out in the framework of the SOEIS (The Self-Organization of the European Information Society) project. The authors wish to thank Dr. Giovanni Russo (University of Utrecht) for his helpful methodological suggestions as well as the SOEIS group for the interesting comments. The third author is also grateful to the Faculty of Statistics (University of Bologna) for the grant assigned to him.

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ANNEX A

In this Annex an extrapolation of the results concerning the sensitivity analysis illustrated in Section 6.3 is displayed (see Tables A.1-A.3). In particular, the variable *Old Output* refers to the local environment score (LES) related to the commercial success (by the firm) predicted by the NN model, while the variables *New1* and *New2* indicate the results - for the NN model - of the sensitivity analysis in order to study the 'transferability factor'. More in details, the variable *New1* (see Table A.1) indicates the output (Business(LES)) of the NN after the 'virtual movement' of the Dutch firms in Italy.

Table A.1. The results of the sensitivity analysis - for the NN model - for Dutch firms (micro level)

Dutch firms Firm code	**Old Output**	**New1 NL → IT**	**New2 NL → UK**	**New1-Old**	**New2-Old**
1	67.48	132.40	76.60	64.92	9.12
2	67.89	130.33	76.28	62.44	8.39
3	80.66	132.14	76.91	51.47	-3.75
4	70.58	138.61	80.61	68.03	10.02
5	69.76	95.60	82.81	25.83	13.04
6	61.12	140.88	76.49	79.76	15.38
7	80.07	127.18	78.69	47.10	-1.37
8	88.22	134.61	85.64	46.38	-2.58
9	47.38	90.24	74.97	42.85	27.58
.	.	.	.	.	.
.	.	.	.	.	.
30	65.48	99.87	75.66	34.38	10.18
31	51.33	91.92	75.84	40.58	24.50
32	75.42	96.43	84.98	21.01	9.56
33	69.22	96.63	84.09	27.40	14.87
Average				**49.93**	**13.71**

These tables are only an extrapolation of the 273 firms, viz. 33 (Dutch), 32 (Italian) and 208 (English) firms. For the sake of space not all the 273 results are presented. The dots indicate that the tables are not complete[♣] .

[♣] The full details are available from the authors.

Table A.2. The results of the sensitivity analysis - for the NN model - for Italian firms (micro level)

Italian firms Firm code	Old Output	New1 IT → NL	New2 IT → UK	New1-Old	New2-Old
34	96.78	107.80	96.37	11.02	-0.41
35	100.22	79.82	84.11	-20.40	-16.11
36	130.85	89.34	65.48	-41.51	-65.37
37	115.88	112.71	97.78	-3.17	-18.09
38	132.47	82.47	95.08	-50.01	-37.39
39	108.33	108.66	96.55	0.32	-11.78
40	105.98	110.99	98.67	5.01	-7.31
41	149.40	124.68	94.11	-24.71	-55.29
42	111.84	100.42	101.86	-11.41	-9.97
.	.	.	.	.	.
.	.	.	.	.	.
62	85.17	26.31	70.03	-58.85	-15.13
63	123.01	40.40	85.83	-82.60	-37.18
64	83.38	25.33	67.44	-58.05	-15.94
65	87.62	28.95	69.80	-58.67	-17.82
Average				**-31.97**	**-20.13**

Table A.3. The results of the sensitivity analysis - for the NN model - for English firms (micro level)

English firms Firm Code	Old Output	New1 UK → NL	New2 UK → IT	New1-Old	New2-Old
66	72.20	38.97	87.35	-33.20	15.15
67	72.60	43.90	88.94	-28.70	16.34
68	72.04	42.56	88.09	-29.42	16.04
69	72.20	38.99	87.35	-33.21	15.15
70	72.20	38.99	87.35	-33.21	15.15
71	91.91	81.63	103.65	-10.28	11.74
72	72.20	38.99	87.35	-33.21	15.15
73	72.20	38.99	87.35	-33.21	15.15
74	72.20	38.99	87.35	-33.21	15.15
.	.	.	.	.	.
.	.	.	.	.	.
270	59.53	18.32	71.37	-41.21	11.84
271	47.85	13.88	64.35	-33.97	16.50
272	84.08	72.78	121.89	-11.30	37.81
273	81.13	64.50	98.60	-16.63	17.46
Average				**-16.6768**	**32.87**