EU KNOWLEDGE ECONOMICS: A SELF-ORGANIZING MAP ARTIFICIAL NEURAL NETWORK ANALYSIS

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The recent enlargements to new Member States are challenging steps forward in the development of the European Union (EU). Such developments, together with the achievement of a single market, require a new approach to the Knowledge economics. Nowadays, the concept of Knowledge as a source of economic development gains popularity, giving rise to the term "Knowledge Based Economies". On the basis of the growing importance of the knowledge, it may be said that only those economies could compete internationally in near future who would develop and integrate the basic ingredients of Knowledge into their economic systems and models: research and development (R&D) activities, human capital, degree of openness to international trade and information and communication technologies (ICT) diffusion. Keeping in mind this view, the aim of the paper is to analyze clusters and distances existing among the EU's member by using the Self-Organizing Map (SOM) artificial neural network methodology. The results seem to confirm the goodness of the underlying theoretical paradigm.

Keywords: economic growth, development, knowledge economics, neural networks.

1. Introduction

The economic implications of the EU enlargement, which reached its culmination in 2007 with the entry of Bulgaria and Romania, following the EU border extension to the East and the Mediterranean Sea in 2004 with the accession of ten new member states[64], are still issues of debate. Preliminary studies highlighted that EU accession provided a boost to growth for new entrants, which – among other things – have benefited from structural funds for infrastructure development, research, firm promotion, environmental protection, tourism, education, etc. In spite of the doubts raised by some observers, the economic impact of enlargement on old member states was also not negligible, particularly as a consequence of trade with Eastern European countries.

The widening of the European Union was indeed aimed at creating a broader and more integrated common market, able to offer economic advantages to old and new member states, by spurring economic growth. Actually, economists have always paid attention to the topic of growth and its main determinants. However, owing to the contrasting conclusions reached by scholars, there remains some disagreement over the identification of growth-determining factors.

In the last few years, scholars have been increasingly focusing on the implications of new knowledge as a product of R&D activities, which would be capable of improving factor productivity and – as a consequence – raising per capita output levels. At the same time, a number of contributions has also been made in studying the role that human capital, the degree of openness to international trade and the information and communication technologies (ICT) may play in knowledge diffusion, generally recognized as the primary engine of growth.

Following the dominant literature, we will argue that the amount of knowledge and the way it is used are the key determinants for productivity, whose increase exerts a positive impact on growth and development of the economic system as a whole.

The main aim of the present paper is to test and demonstrate the robustness of the underlying paradigm, through the analysis of the economic structure of the EU's member states in 1998 and 2005, respectively. In this regard, a brief overview of the relevant literature on economic growth, with a review of empirical evidence on its possible determinants, is provided (see par. 2). In the second section, a SOM neural network methodology, chosen as a tool for research, is set out (see. par. 3); to this effect, an analysis is made in order to spot patterns of multidimensional similarity among the EU's member states (see par. 4). Finally, brief concluding remarks are made on the main results achieved by the analysis (see par. 5).

2. Key determinants of economic growth and development

Recently, a soaring number of researches have been conducted on economic growth and its determinants. In the last few years, a growing interest has aroused with reference to knowledge contribution to increase in total factor productivity (TFP) and to consequential long-run sustainable growth.

As highlighted in previous studies (Mattoscio 2005, Mattoscio & Colantonio 2005, 2006 and 2007, and Mattoscio, Colantonio & Carlei 2007), economic research on knowledge dynamics has been carried out along different lines.

Particularly, several authors (among who Romer 1992, Aghion & Howitt 1992, 1998, now in 2004) have drawn attention to innovation systems and to R&D activities, which lead to new technology creation and may eventually positively affect per capita output increase. Even more recently, other researches have showed that innovation or technical knowledge development have a significant positive effect on economic growth and productivity increase (see Lederman & Maloney 2003, Guellec & van Pottelsberghe 2001 and Adams 1990).

Starting from the most important contributions of endogenous growth theory, technological progress comes to be linked to investments in human capital. This concept is introduced by the economists from the Chicago School in the Sixties, Schultz (see, for example, 1961) and Becker (see, for instance, 1962 and 1964), to define the skills embodied in people. The subsequent work of Romer (see, for example, 1986 and 1990) and Lucas (see, for example, 1988), another leading figure in the Chicago School, further stresses the effects, both quantitatively and qualitatively, of human capital on growth rates. Nowadays, hundreds of empirical studies on economic growth include human capital measures (see, for example, Barro 1991, Cohen & Soto 2001 and Hanushek & Kimko 2000).

Grossman and Helpman (1991) develop an approach of growth in the context of an economy open to international trade, in which they assume that technological know-how may be imported from abroad. Similarly, Coe and Helpman (1995) show, for a sample of advanced countries, that both domestic and foreign R&D activities have a positive effect on TFP; such a relationship is even more significant in presence of a higher degree of openness to international trade. Several more empirical studies, like those carried out by Frankel and Romer (1999), Gallup, Radelet and Warner (1999), Irwin and Tervio (2002), and Dollar and Kraay (2001), highlight the positive relationship between openness to foreign trade and growth rates.

Another channel facilitating technological diffusions is represented by foreign direct investments (FDI) (see Barrel & Pain 1997). In 1993, Romer has already advanced such an hypothesis, implying that FDI might result in substantial positive spillovers not only for the single benefiting firms, but also for the economy as a whole (in this light, see also Rappaport 2000).

A larger interconnection, a higher processing speed and a wider knowledge access are also encouraged by the new ICT. Though not directly generating innovations, ICT are regarded as the backbone of the *knowledge economics* and have been recognized as an effective instrument for promoting economic growth and development. Owing to their relatively low cost of use and their ability to scale distances down, ICT have revolutionized information and knowledge transfer all over the world.

In such a regard, a number of researches show that the production ICT has made a major contribution to economic growth (see Jorgenson & Stiroh 2000, Oliner & Sichel 2000, Whelan 2000, Schreyer 2000 and Pilat & Lee 2001). Several studies have provided empirical evidence that productivity gains are also due to the simple use of ICT, at least at a country-specific level. As to the United States, for example, the Economic Report of the President (Council of Economic Advisors 2000 and 2001), Whelan (2000), Oliner and Sichel (2000) and Jorgenson and Stiroh (2000) attribute a large part of increase in TFP to ICT-using sectors rather than to ICT-producing sectors. With reference to Australia, there exist evidence indicating that increased productivity levels are coupled with a larger use of technologies including ICT (Productivity

Commission 1999). Other sectorial studies suggest that investments in ICT exert a positive impact on whole system productivity (for example, as to the distribution sector, see Readon *et al.* 1996 and Broersma & McGuckin 1999). Brynjolfsson and Kemerer (1996) and Gandal *et al.* (1999) find the existence of positive spillovers stemming from ICT capital at the single firm level. In addition, some authors (see, for example, Solow 1987) are skeptical towards such a perspective, though their analyses do not actually invalidate the critical assumptions on the crucial role of ICT in growth dynamics.

In a nutshell, by referring to the above-mentioned contributions, we might postulate the existence of four preconditions necessary for knowledge to be the real engine of growth:

- an effective innovation system, made up of firms, research centers, universities, and so forth, capable of raising the stock of knowledge and to absorb it and adjust it to local needs;
- an educated and qualified population, able to create, share and use knowledge;
- a good degree of openness to foreign trade, encouraging imports of technical knowledge developed abroad;
- an adequate ICT infrastructure, facilitating information and knowledge transfer.

In the light of this theoretical framework, a number of indicators representing the main aspects of the knowledge economics have been detected.

The benchmark years under scrutiny are chosen as a consequence of the dual need to make use of complete and reliable datasets and to assess the economic performances of EU countries during the transitory period from industrial to post-industrial society till the New Economy experience (see Felice & Mattoscio 2005).

In carrying out the analysis, we mainly used Eurostat database[65], properly integrated with alternative official sources (particularly UN[66]) in order to fill missing values[67]. The choice of integrating different databases is determined by the need to have complete and reliable data at our disposal. In such a respect, by means of an empirical analysis concerning EU's member states, we will investigate the economic performances in 1998 and 2005, respectively.

The analysis we undertake is firstly concerned with a set of three indicators associated to the degree of a country's socio-economic development. In this respect, the first variable considered is "*GDP per capita (PPP US$)*"[68], which accounts for the differences in general price levels in different countries as well as for average exchange rates recorded by IMF, thus allowing a proper comparison in per capita income terms.

A second indicator recording socio-economic development of countries is the "*Human Development Index*", a composite measure developed within the *United Nation Development Programme*, which may assume values between 0 and 1. It allows to classify countries according to criteria linked to survival expectancies, educational attainment reached on average and life quality. Basic dimensions are identified by:

1. average life expectancy at birth, as a measure of a healthy and long life;
2. "Education Index"69, combining adult literacy (with a weight of two-thirds) and the number of students enrolled at different levels of education (with a weight of one-third), as a measure of the degree of education;
3. per capita GDP, which refers to the standard of life.

The third and last indicator of socio-economic development is "Energy intensity of the economy - Gross inland consumption of energy divided by GDP (at constant prices, 1995=100) - kgoe (kilogram of oil equivalent) per 1000 euro". This variable measures the ratio between Energy consumption (in kilogram of oil equivalent) and GDP (expressed at constant prices of 1995): it provides an indicator of a country's energy efficiency.

After illustrating some indicators concerning the socio-economic development of countries, we focus our attention on variables condensing innovation activity. It must be recalled that economic differences observed among countries may be explained – to a certain extent – in the diverse capability of generating new knowledge.

Among the different indicators available in this regard, we considered "*Total intramural R&D expenditure (Euro per inhabitant)*"), independently of public or private source of funds. In order to make comparisons between countries, the considered values have been expressed in per capita terms. A second indicator concerning technological progress is represented by "*Human Resources in Science and Technology (percentage of total population)*". The third and last variable considered for assessing technological development is "*High-technology exports (% of GDP)*". As happens with domestic innovation activity, value can also be created by exporting or selling new technologies abroad.

Among the variables usually employed for specifying human capital is included "Graduates (ISCED 6) from science, mathematics, computing, engineering, manufacturing & construction fields per 1000 of the population aged 25-34". Another relevant variable is the "Ratio of Students to teachers (ISCED 3)" at secondary level, which is deemed to be a measure human capital quality by economic literature. The last indicator representing a particular aspect of human capital, "Total public expenditure on education as % of GDP", was chosen in order to render comparable values of countries with different structural features.

As underlined above, less developed countries may narrow the technological gap from more advanced economies, by importing or imitating technologies produced abroad; in this respect, the degree of openness to international trade and the flow of foreign direct investments appear to play a major role in growth dynamics.

The first two indicators we considered are "*Imports of goods and services (% of GDP)*" and "*Exports of goods and services (% of GDP)*" (see tabb. 1 and 2). The third and last indicator concerning the degree of openness to international trade is represented by "*Net foreign direct investment inflows (% of GDP)*". This variable is obtained as the difference between incoming capital flows and outgoing capital flows considered as a percentage of GDP.

Empirical studies confirm the existence of positive effects of technology production and diffusion on economic growth. As a result, we consider three variables as proxies of the ICT stock: "*Telephone mainlines (per 1000 people)*", "*Cellular subscribers (per 1000 people)*" and "*Internet users (per 1000 people)*" (see tab. 1 and 2).

3. Working methodology

In this paragraph, we introduce the artificial neural network methodology, chosen to better represent economic clusters and gaps with respect the EU's member states.

3.1. Non linear clustering through SOM neural networks

Self Organizing Map is amongst the most important neural network architectures. It has been mainly developed by Teuvo Kohonen (Kohonen 1995).

In SOM networks the characterizing element is a layer, called Kohonen layer, made up of spatially ordered Processing Elements (PEs). Such a PE layer evolves during the learning, specializing each PE positions as indicators of important statistic features of input data. This spatial organizing process for important statistic features of input data is also known as Feature Mapping. SOM realize the feature mapping by an unsupervised learning technique.

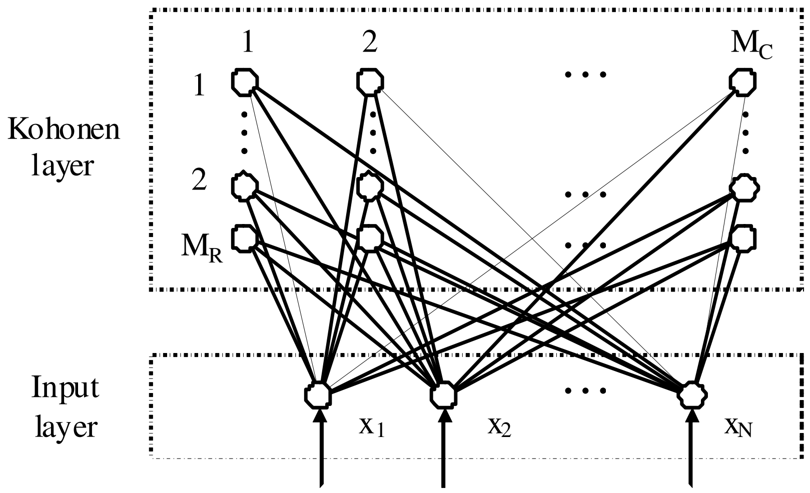
Mapping made up by SOMs has interesting characteristics, in fact it's not random, but it preserves topological relationships of input data and code them in a complex way into Kohonen map (Carlei *et al.* 2006).

A first analogy between the biological system and the SOMs artificial one is based on the macroscopic way of working of the brain. During the growth, in human brain it happens a splitting into zones that act according to different input stimuli. Similarly in SOMs, during the learning, the Kohonen map splits itself into different regions, each responding to a particular region of the input space.

Some are constituted by two layers: a mono-dimensional input one, with a PE for each of the N input components $X = (x_1, x_2, \ldots, x_N)$, and a layer, typically bi-dimensional, said Kohonen layer, made of M = MC · MR PE organized in a grid of MC PE per row and MR PE per column (see fig. 1). We will indicate the generic PE in the Kohonen layer with PEr with $r = 1, 2, \ldots, M$.

Input layer is completely connected to the Kohonen one: each PE belonging to the Kohonen layer receives values from all the PE of the input layer.

Fig. 1 – SOM with N entries and M=MC•MR Pe in the 2-D Kohonen layer



Source: our own representation

To the generic PE in the Kohonen layer is associated a vector whose element are the weights relative to connections with the input PE. The vector associated to the generic PEr in the Kohonen layer is indicated with $W_r = (w_{r1}, w_{r2}, \ldots, w_{rN})$. Input layer is just a buffer layer so its PE won't operate any change in the input value they receive. Output is computed by the Kohonen layer. In this layer the PE work in a competitive way. In its basic version, each time an input is processed a winning PE is selected. In this case the output is the PE position in the grid, so it takes discrete values. This operation is also called vectorial quantization.

Anyway, Kohonen layer can't be defined simply as an output layer. It's in fact the core layer of the network used by the competitive algorithm.

3.2. SOM learning and map construction

During this process the input vectors (learning set) are introduced both in cyclic or random way, till an equilibrium state is attained.

SOM learning is unsupervised, i.e. during this phase there are no constraints saying whether an output is right or not for the input data: the algorithm is such that the network self-organize itself correcting the weights values each time a new input is processed.

Closeness of vectors can be computed in several different ways. A first way is using the scalar product C_r between W_r and X, choosing PE_s as the PE which maximizes this value:

$$PE_s: \quad C_s = \max_{r \in [1..M]} \left\{ C_r = X \cdot W_r = \sum_{i=1}^{N} x_i \cdot w_{ri} \right\} \qquad \textbf{[1]}$$

Another way to measure closeness is through Euclidean distance D_r between W_r and X, choosing PE_s as the PE which minimizes it:

$$PE_s: \quad D_s = \min_{r \in [1..M]} \left\{ D_r = \| X - W_r \| = \sqrt{\sum_{i=1}^{N} (x_i - w_{ri})^2} \right\} \qquad \textbf{[2]}$$

When the winning PE has been determined, the weights for the PE itself and for those who are close to it physically in the Kohonen layer (this set is called PE neighbourhood) are updated.

Updating the weights of the entire neighbourhood is a feature that differentiates it in comparison to other competitive algorithms. It's in fact, as we shall see, essential to preserve topological features of input data throughout the mapping.

Several definitions of neighbourhood are available. Its definition is based on the Euclidean distance d, defined on the Kohonen layer, between the generic PE_r and the winning PE_S. Basically, we define a function h(d) describing how the generic PE_r will update under the updating W(d) of the associated weight vector W_r. This updating is of the following type:

$$\Delta W(d) = h(d) \cdot (X - W_r) \qquad \textbf{[3]}$$

Usually, h(d) function assumes positive values, has a maximum for d = 0 and is strictly decreasing. Therefore, every time values are updated, PE weight vectors are moved toward the input data, with less and less intensity as the distance from the winning PE increases. Kohonen layer is therefore a matrix of PEs which are competing and whose associated vectors tend, iteration by iteration, to assimilate to the different input patterns.

A first example for neighborhood function h(d), which shows all the general characteristics exposed above, is the Gaussian function:

$$h(d) = He^{-\frac{d^2}{2\sigma^2}} \qquad \textbf{[4]}$$

Such a function is defined on the entire Kohonen layer. As H and σ vary, the effects on the PE change and so do some of the learning features.

The parameters used in the functions are usually changed iteration after iteration, so to optimize the features of learning.

3.3. Clusters mapping from SOM features

As we already mentioned, SOM map an input space to a Kohonen layer showing very interesting features. Such features make this architecture as one of the most interesting within neural networks, and they results particularly indicated for the aim of this work.

The first feature of SOM mapping is to logically split the input space into clusters. We have already told in fact, that Kohonen net maps each point of the N-dimensional space into a point of the discrete output space. For each PE in the Kohonen layer there is a set of input data which make it the winning. These input points define a region.

Another fundamental feature of the learning of the SOM is self-organizing and input data ordering; this gives particular characteristics to the mapping. In order to show it, it results very useful visualizing the mapping performed by the Kohonen layer, using the so called virtual network (Buscema M. & Semeion Group, 1999). Such a network can be built in the input space drawing segments joining the points representing contiguous PE in the Kohonen layer.

Before of the learning, the weighs vectors are dispose according to a topology bounded just by the initialization criterion. During the learning the algorithm tends to modify the vectors of weight, and this appears as deformation of the virtual network.

Anyway, the neighbourhood is defined in the two dimensions space made up of PE of the Kohonen layer whatever are the dimensions of the input space. The learning criterion can't be seen geometrically as invariant respect to the input space dimensions. We can better understanding what it means in term of virtual network deformation, and so of mapping, distinguishing two cases.

The first case, the simpler one, is when input space dimensions and Kohonen layer dimension agree. The second case, the most complicated, is when the dimension of the input data are greater than the Kohonen layer one. There is a so called dimensions conflict. As in the previous case, points of the input data are mapped into PE. But in this case, what is mapped into close PE is a closeness that is defined on a higher dimensional space. A reduction of dimensions occurs. With this reduction of the input space, the principal component characterizing the data, i.e. the ones with highest variance in the input space, prevail. In other words we can say that only the main topological relationships between input data are preserved, being extracted and mapped into the PE grid.

4. A data analysis

In this section, we address the cluster dynamics emerging during the 1998-2005 interval, within which EU enlargement process took place. The explaining features of cluster evolution and the causal relationship between topical variables of the knowledge economics are further investigated.

The topological clustering, obtained by means of the above considered variables with SOM algorithm, provides results which are to be interpreted on the basis of two informative levels.

At a first level of analysis, we explore the scenario transformation of European countries during the transition phase from 1998 to 2005.

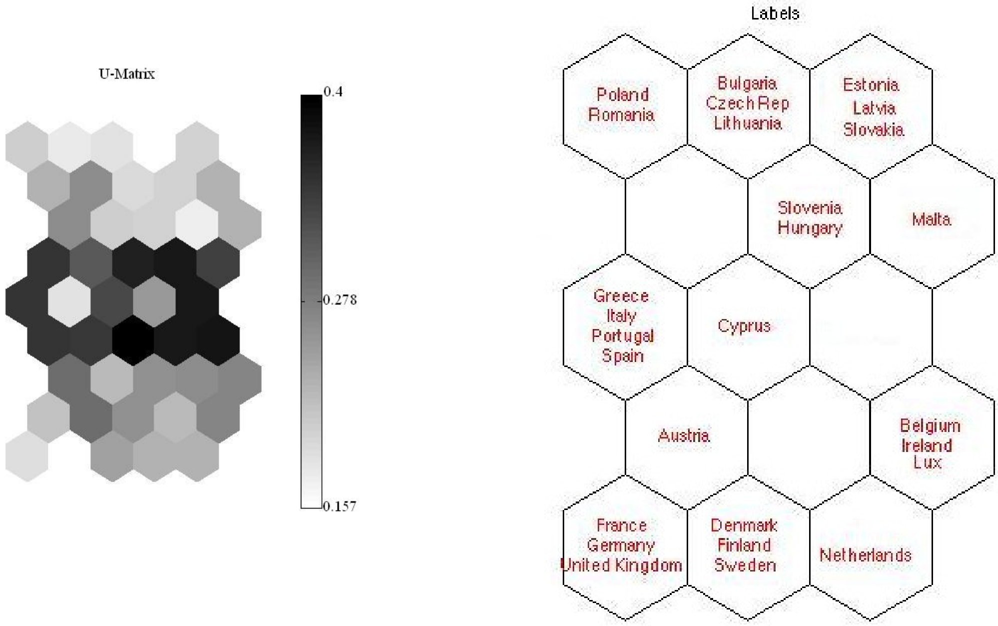
The study of these two historical moments allows to spot the some changes occurring in the relationships among countries, as highlighted by the alteration of topological structure of the Kohonen layer. In 1998, it is possible to detect three clear-cut groups of countries, having in common geographical features and socio-economic variables.

The first group (see fig. 2) is made up of Eastern countries and is situated in the hexagonal cells of the upper part of the map. The second group, lying slightly lower, is represented by Mediterranean countries, while the countries of Central and Northern Europe belong to the third cluster. The distance among these groups in terms of multidimensional similarity is rather wide: in the map on the left, it is possible to spot a U-Matrix (a unified matrix of distances) emerging out of the darker hexagons of Mediterranean countries, which shows a wider distance between Mediterranean and Eastern countries as well as Central-Northern and Mediterranean countries, thus rendering the latter a “middle land” among the three groups.

The 1998 situation is therefore characterized by three homogeneous clusters both from a geographical and a socio-economic point of view. Probably, this is the last picture of Europe before the Union and it resembles the European region as inherited from the opposition dynamics between the East and the West during the era of the Berlin Wall and from the socio-economic features of Western Europe, split between Mediterranean countries and states from Central and Northern Europe.

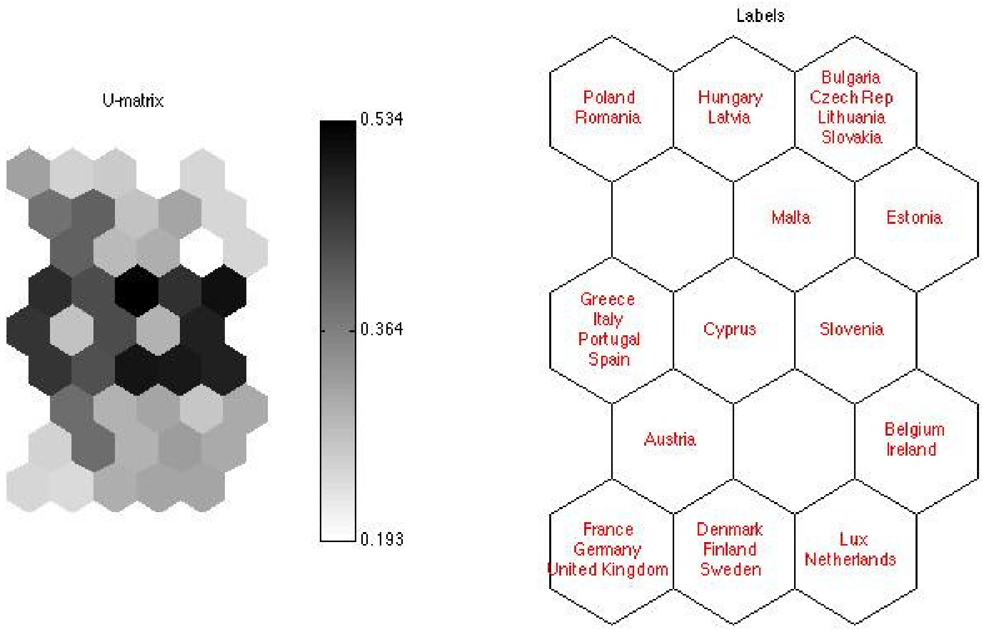
The 2005 situation (see fig. 3) large confirms the cluster topology emerged in 1998. Only the cluster of Eastern countries, particularly close-knit in 1998, turns out to be divided into two parts in 2005. In the upper part of the map, we find many Eastern countries, holding the same positions of the previous years; Slovenia and Estonia has progressed towards the Western model, moving downwards the map. But, in general, the used model seems to confirm a certain stability in clusters and distances among the EU’s member states, basing on the relevant aspects of the knowledge economics.

Fig. 2 – SOM cluster in 1998



Source: our own elaboration

Fig. 3 – SOM cluster in 2005



Source: our own elaboration

If we focus the attention on the basic structure of the maps, both in 1998 and 2005, moving from the upper part to the lower one, we can observe an increase in the following features:

- GDP per capita

- Human Development Index
- Energy intensity of the economy
- Total intramural R&D expenditure
- Human Resources in Science and Technology
- High-technology exports
- Telephone main lines
- Cellular subscribers
- Internet users

In other words, similarities and distances on a virtual vertical axis mainly seem to be due to socio-economic development, R&D activities and ICT diffusion (see also fig. 4 and 5).

Moreover, moving from the left part to the right part of the two maps, we can observe an increase in the following features:

- Exports of goods and services
- Imports of goods and services
- Net foreign direct investment inflows

Consequently, similarities and distances on a virtual horizontal axis mainly seem to be linked to the openness to international trade (see also fig. 4 and 5).

Some of these indicators confirm a strong tendency to overlapping compared to other proxies. Other variables, particularly those related to human capital, exhibit non-linear relationships with respect to the order established by the other indicators.

This is particularly true, for example, if we take into account variables such as *Total public expenditure on education* and *Ratio of students to teachers*: they do not appear to be overlapping, since the latter indicator is influenced by the sheer number of students. Actually, some countries, though with low investments in education (also owing to the low GDP per capita level) show a good ratio of students to teachers, probably due to a relatively low number of students.

As said above, during the 1998-2005 period, the development indicators do not show substantial differences, confirming on the one hand the leadership of Nordic and central countries and the median position of the Mediterranean ones, and on the other hand the bottom position of recently acceded EU member states. The latter, however, are progressively departing from the cluster of 1998, in particular with Estonia and Slovenia slowly joining Italy, Spain, Greece and Cyprus.

Fig. 4 – SOM features analysis in 1998

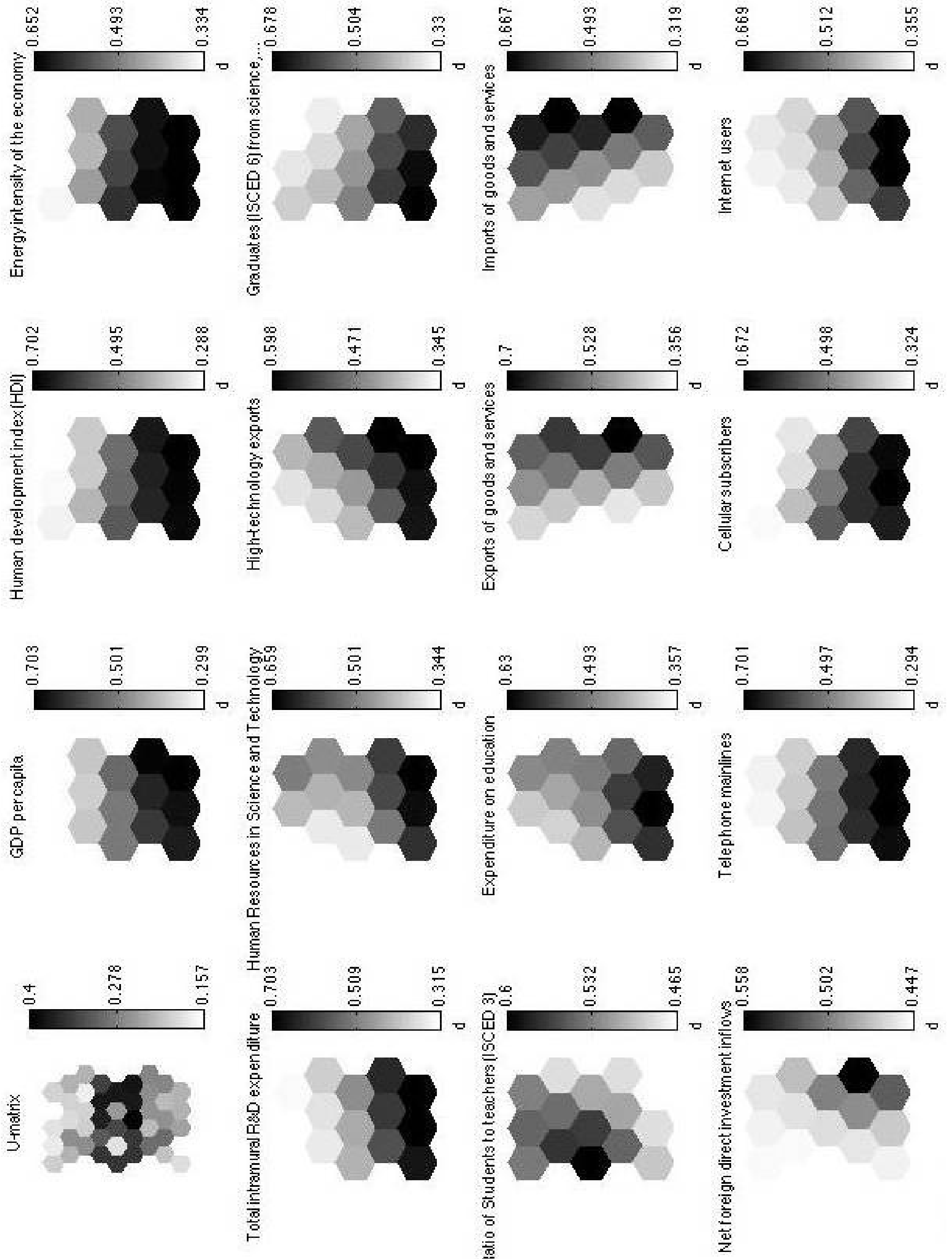
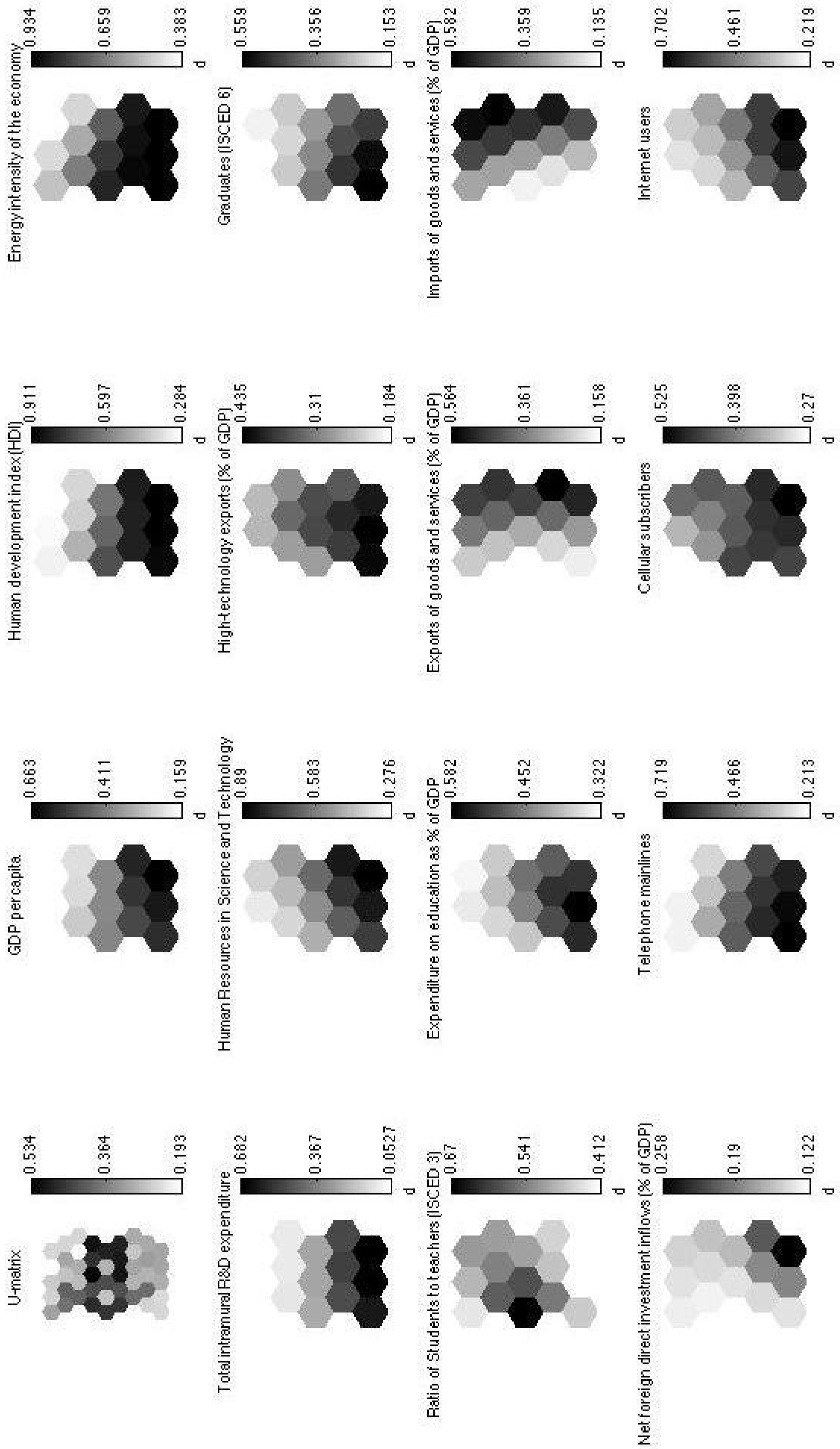


Fig. 5 – SOM features analysis in 2005



Source: our own elaboration

5. Concluding remarks

Economic theory assumes that knowledge is conducive to increase in TFP, thus exerting positive effects on economic growth. However, differently from traditional factors of production, knowledge does not wear out with use. As a result, knowledge creation, adoption and diffusion, in its many forms, may represent an engine for growth and development of countries.

However, some conditions must be complied with in order for knowledge to be a positive determinant of growth. First, widespread innovation and capability of adopting advanced technological solutions are required. Second, a crucial role seems to be played by human capital, though further efforts must be made to find adequate indicators for its measurement. Finally, knowledge diffusion within a country can be furthered by a higher degree of openness to foreign trade and by the presence of modern infrastructures for information and communication.

Consistently with the underlying theoretical framework, this paper was aimed at highlighting the distances among EU'S member states, focusing the attention on the growth levels and on the main determinants of economic development both in 1998 and 2005.

By means of the adoption of SOM artificial neural networks, we showed that recently acceded EU countries, albeit beginning with low levels of economic development, have grown rapidly, thus reducing the gaps from more advanced countries. In other words, the changes brought about by enlargement, in particular wider market competition, provided a considerable contribution to economic convergence of new members, which have consequently laid the foundations for a modern knowledge-based society.

The model we used has basically confirmed the evidence gained in previous analyses conducted with different methodologies and data (see Mattoscio & Colantonio 2007) or on different data (Mattoscio, Colantonio & Carlei 2007): we can therefore reassert the robustness of the underlying theoretical paradigm, which considers the dynamics between technological progress, human capital, international relationships and ICT diffusion as the main engine of growth for a country.

Nevertheless, being the present model based on a comparative static analysis, further investigation is required to better explore the dynamics of the above mentioned factors on the growth of an economic system.

Tab. 1 – Data base 1998

	GDP per capita (PPP US$) a	Human development index (HDI) value a	Energy intensity of the economy - Gross inland consumption of energy divided by GDP (at constant prices, 1995=100) - kgoe (kilogram of oil equivalent) per 1000 euro b	Total intramural R&D expenditure (Euro per inhabitant) b	Human Resources in Science and Technology (percentage of total population) b	High-technology exports (% of GDP) b, c	Graduates (ISCED 6) from science, mathematics, computing, engineering, manufacturing & construction fields per 1000 of the population aged 25-34 b	Ratio of Students to teachers (ISCED 3) b, c	Total public expenditure on education as % of GDP b	Exports of goods and services (% of GDP) b	Imports of goods and services (% of GDP) b	Net foreign direct investment inflows (% of GDP) a, g	Telephone mainlines (per 1000 people) a, i	Cellular subscribers (per 1000 people) a, i	Internet users (per 1000 people) a
Austria	23166	0,908	144,83	423,6	16	4,96	0,6	10	5,80	41,7	40,3	2,8	491	249	21,20
Belgium	23223	0,925	248,83	416,6	23,4	5,90	0,4 d	13,8 e	5,19 e	74,7	70,4	8,4	500	173	20,58
Bulgaria	4809	0,772	2250,66	7,8	17,4 d	0,99	0,1	11,6	4,28	47,1	46,8	3,3	329	15	1,23
Cyprus	17482	0,886	301,90	27,6	21,7 c	1,99	0,0 d	13	5,61	49,8	50,7	2,2	585	168	7,94
Czech Republic	12362	0,843	946,52	61,6	19,1	4,28	0,3	13,1	3,95	54,2	55,3	4,5	364	94	8,41
Denmark	24218	0,911	140,67	599,2	26,1	5,32	0,3	11,7	8,30	38,3	36,2	3,8	660	364	56,29
Estonia	7682	0,801	1495,26	20,6	27,4	7,60	0,1	10,6	5,71	75,2	85,1	11,2	343	170	16,62
Finland	20847	0,917	288,93	647,7	28,8	7,95	0,9	16,6	6,26	38,4	29,6	9,0	554	572	89,17
France	21175	0,917	197,66	469,5	21,4	6,29	0,7	12,7	5,95	26,2	23,7	2,0	570	188	8,57
Germany	22169	0,911	170,20	540,4	26,3 c	4,08	0,7	13,9	4,50 c	28,7	27,3	0,9	567	170	17,67
Greece	13943	0,875	272,67	73,2 c	14,4	1,09	0,4 e	10,7	3,48	19,8	28,2	0,6	522	194	4,71
Hungary	10232	0,817	661,91	27,7	15,2	12,01	0,4	10,3	4,59	61,9	63,4	4,0	336	105	9,47
Ireland	21482	0,907	196,79	263,5	18,7 c	34,16	0,6	16	4,82	86,7	74,9	8,3	435	257	15,17
Italy	20585	0,903	191,36	200,3	12,6	1,89	0,2	10,2	4,65	25,2	22,1	0,2	451	355	6,71
Latvia	5728	0,772	740,48	10,0	19,1	1,07	0,1	11,9	5,85	46,6	58,6	4,3	302	68	5,83
Lithuania	6436	0,789	1592,39	15,3	31,9	0,96	0,1	13,8 e	5,99	45,5	56,9	8,7	300	72	2,65
Luxembourg	33505	0,908	197,91	839,3 d	22,7 c	19,25	0,4 e	9,9	5,19 e	127,5	111,1	364,0 h	692	308	18,26
Malta	16447	0,865	347,70	259,9 e	13,6 d	43,45	0,0 d	32,5	4,82	78,0	83,5	3,7	360	59	4,79
Netherlands	22176	0,925	211,71	435,7	27,9	13,71	0,4	17,7	4,82	62,6	57,9	8,3	593	213	39,75
Poland	7619	0,814	792,25	26,5	14,5	0,60	0,2	16,9 d	5,02	26,0	30,8	3,2	228	50	3,37
Portugal	14701	0,864	239,15	68,4	9,9	1,28	0,6	8,5 d	5,36	29,0	37,9	1,6	413	309	5,60
Romania	5648	0,770	1638,27	8,4	11,5	0,68	0,4 e	12,9	3,36 c	22,6	30,6	5,4	167	29	1,05
Slovakia	9699	0,825	997,62	28,9	16,6	2,07	0,3	13,8	4,53	59,0	69,8	2,3	286	87	4,10
Slovenia	14293	0,861	371,76	130,1	17	2,01	0,4	12,9	5,19 e	52,8	54,2	0,8	375	84	11,51
Spain	16212	0,899	223,59	118,4	17,9	1,58	0,3	12,9	4,42	26,7	26,9	2,0	414	179	7,79
Sweden	20659	0,926	248,52	904,6 f	27,7	7,55	1,1	15,5	7,69	42,4	36,2	8,5	674	464	42,86
United Kingdom	20336	0,918	242,71	391,3	22,5 c	7,37	0,6	18,7	4,77	27,0	27,8	4,7	556	252	24,59

Notes: **a.** Source: HDR; **b.** Source: Eurostat; **c.** Value in 1999; **d.** Value in 2000; **e.** Sample mean; **f.** Estimated value; **g.** Our computations on HDR data; **h.** Our estimates; **i.** Data refers to the most recent available year between 1996 and 1998.

Tab. 2 – Data base 2005

	GDP per capita (PPP US$) a	Human development index (HDI) value a	Energy intensity of the economy - Gross inland consumption of energy divided by GDP (at constant prices, 1995=100) - kgoe (kilogram of oil equivalent) per 1000 euro b	Total intramural R&D expenditure (Euro per inhabitant) b	Human Resources in Science and Technology (percentage of total population) a	High-technology exports (% of GDP) b	Graduates (ISCED 6) from science, mathematics, computing, engineering, manufacturing & construction fields per 1000 of the population aged 25-34 b, c	Ratio of Students to teachers (ISCED 3) b, c	Total public expenditure on education as % of GDP b, c	Exports of goods and services (% of GDP) a	Imports of goods and services (% of GDP) a	Net foreign direct investment inflows (% of GDP) a	Telephone mainlines (per 1000 people) a	Cellular subscribers (per 1000 people) a	Internet users (per 1000 people) a
Austria	33700	0,948	149,32	721,8	36,8	12,8	0,7	11,0	5,44	53,0	48,0	3	450	991	486
Belgium	32119	0,946	205,7	531,5	47,5	8,7	0,5	9,2	5,99	87,0	85,0	8,6	461	903	458
Bulgaria	9032	0,824	1582,41	13,7	27,5	4,7	0,1	12,1	4,51	61,0	77,0	9,8	321	807	206
Cyprus	22699	0,903	246,92	73,7	43,3	46,3	0,1	11,3	6,70	47,9 c	50,3 c	7,3	554	949	430
Czech Republic	20538	0,891	823,38	138,6	29,8	12,9	0,5	12,6	4,37	72,0	70,0	4,1	314	1151	269
Denmark	33973	0,949	114,12	941,3	48,2	21,6	0,6	13,4	8,47	49,0	44,0	2	619	1010	527
Estonia	15478	0,860	966,92	77,2	42,7	17,6	0,4	12,0	4,98	60,0	90,0	22,9	328	1074	513
Finland	32153	0,952	241,46	1045,3	48,0	25,2	1,0	16,2	6,42	39,0	35,0	2,1	404	997	534
France	30386	0,952	185,47	585,3	46,1	20,0	0,6	10,4	5,81	26,0	27,0	3,3	586	789	430
Germany	29461	0,935	157,02	675,6	36,9	16,9	0,8	13,9	4,59	40,0	35,0	1,1	667	960	455
Greece	23381	0,926	236,54	104,1	29,4	10,2	0,5	8,4	3,84	21,0	28,0	0,3	568	904	180
Hungary	17887	0,874	543,58	82,9	27,5	24,5	0,1	12,3	5,43	66,0	69,0	5,9	333	924	297
Ireland	38505	0,959	143,92	494,0	43,6	16,0 f	0,6	14,3	4,72	83,0	68,0	-14,7	489	1012	276
Italy	28529	0,941	190,67	266,8	27,7	7,8	0,4	11,5	4,58	26,0	26,0	1,1	427	1232	478
Latvia	13646	0,855	644,81	31,5	31,7	5,3	0,1	12,1	5,07	48,0	62,0	4,6	318	814	448
Lithuania	14494	0,862	949,13	45,8	42,3	6,1	0,3	8,3	5,20	58,0	65,0	4	235	1275	358
Luxembourg	60228	0,944	189,85	1023,4	46,3	11,8	0,5	9,0	3,87	158,0	136,0	301,3	535	1576	690
Malta	19189	0,878	269,9	63,7 d	30,4	53,5	0,5	10,1	4,86	71,0	82,0	4,8 g	501	803	315
Netherlands	32684	0,953	195,55	540,7 d, e	48,8	30,1	0,4	15,8	5,16	71,0	63,0	6,5	466	970	739
Poland	13847	0,870	584,7	36,3	31,5	3,8	0,3	13,5	5,41	37,0	37,0	3,2	309	764	262
Portugal	20410	0,897	241,43	114,1	24,7	8,7	1,0	7,3	5,29	29,0	37,0	1,7	401	1085	279
Romania	9060	0,813	1164,89	15,1	19,4	3,4	0,2	16,8	3,29	33,0	43,0	6,7	203	617	208
Slovakia	15871	0,863	868,59	36,1	27,8	7,3	0,4	14,2	4,19	79,0	83,0	4,1	222	843	464
Slovenia	22273	0,917	320,48	206,7	37,8	4,6	0,6	14,3	5,85	65,0	65,0	1,6	408	879	545
Spain	27169	0,949	219,23	236,9	43,0	7,1	0,4	8,0	4,25	25,0	31,0	2	422	952	348
Sweden	32525	0,956	204,34	1241,1	47,9	16,7	1,8	14,0	7,18	49,0	41,0	3	717	935	764
United Kingdom	33238	0,946	202,63	529,9	41,9	28,0	0,9	12,6	5,25	26,0	30,0	7,2	528	1088	473

Notes: **a.** Source: HDR; **b.** Source: Eurostat; **c.** Value in 2004; **d.** Estimated value; **e.** Provisional value; **f.** Sample mean; **g.** Sample mean (with the exclusion of outliers Ireland and Luxembourg).

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