THE EUROPEAN COMPLEX KNOWLEDGE

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Abstract: *Nowadays, it has been besetted with knowledge input and output measurement instead of analyze the quality of the knowledge produced. Since knowledge become central into capitalistic production processes, the competitive advantage of countries is the principal engine for the production of high-value, non-ubiquitous and complex knowledge (see Dicken, 2007). The aim of the present study is to measure the knowledge complexity of the European countries from 2004 to 2013, designing the knowledge evolution and distribution. One consequent intention is to examine in which way the spatial knowledge diffusion might be connected to complexity. To achieve these purposes, we identified the presence of the European country-tech knowledge network, used as starting point to compute the Knowledge Complexity Index, in which the technological classes are composed by the countries having an relative technological advantage in terms of patent spread. Subsequently, we used two distinct types of statistical analysis: the first, based on non-linear clustering with Self-Organizing Map (SOM hereafter) neural network, for evaluating the performance development of the European countries between 2004 and 2013, where, for example, Eat countries, located at the top of the map, show low values in almost all considered variables; and the second one, based on the Knowledge Complexity Index (KCI hereafter) of technological classes, for quantifying the European knowledge complexity; describing the possible spatial patterns and transformation of the European knowledge. What emerges from the present study is an inactive spatial state of art, in which only the Northern European countries produce the most conglomerate knowledge and technologies. In this structure, it is necessary to stress out that what affirmed previously could be considered the basis for the improvement and the achievement of the specific country's innovation policy. However, under complex knowledge terms, the previous innovation policies might be assimilated with a useful tool for the increment of that technologies that present more complexity than the original ones.*

Keywords: *network analysis; neural network; country performance; Europe.*

JEL Classification: *010; 030.*

1. Introduction

Nowadays, knowledge networks give a wide range of opportunities for stimulating knowledge creation, due to the facilitated access to information and knowledge distribution through network links and indirect paths. This framework is possible since central players perform as hubs for knowledge diffusion process: they spread knowledge through various connected actors and knowledge flows between diverse unconnected patterns, carrying out as an information and knowledge *gatekeepers*. As a consequence, knowledge has become central into capitalistic production

processes: the competitive advantage of countries is the principal engine for the production of high-value, non-ubiquitous and complex knowledge (see Dicken, 2007). For that reason, knowledge is considered spatially close, difficult to create or to move outside its productive space: most of the theoretical researcher put their attention on the knowledge economy instead of the absence of the knowledge produced in a country. One possible explanation, according to Pavitt (1982), could be the absence of accurate knowledge and technological measures. Recently, some authors, like Boschma et al. (2015) and Rigby (2015) have tried to analyze structures that might pilot the knowledge development trajectories via the technological abandonment and diversification. These type of investigation were encouraged by Jaffe (1986), who provide a technological distance between firms estimation; and Kogler et al. (2013), who used patent data for the technological classes distance measurement. So, which countries detain the most valuable knowledge? Answering to this question could be hard because, according to Bult (1982), one of the principal reason why the researchers have not so familiarity with the knowledge composition is the inaccurate measurement of the knowledge and technology. In fact, four-years studies have started to investigate this type of phenomenon in deeply. In these studies, it was used patent data to size the distances between classes of technologies providing a visualization of local knowledge space and, at the same time, an exploration on how the previous mentioned structure might guide the local trajectories of possible knowledge development through achievable technological diversification patterns.
The prime aim of the present paper is to try to estimate the knowledge complexity of the European countries from 2004 to 2013, designing the knowledge evolution and distribution. One consequent intention is to examine in which way the spatial knowledge diffusion might be connected to complexity. To achieve these purposes, we identified the presence of the *European country-tech knowledge network*, and subsequently, we used two distinct types of statistical analysis: the first, based on non-linear clustering with SOM neural network, for evaluating the performance development of the European countries between 2004 and 2013; and the second one, based on the KCI of technological classes, for quantifying the European knowledge complexity.
The present paper is structured as follows. Section 2 shows in which way the concepts in the Introduction could be able to work using patent reports; the statistical-topological tool, the SOM; and network-based techniques, describing the KCI construction process. Following, Section 3 shows statistical and visual evidences about how the relatedness and the knowledge complexity have shaped the different configuration in Europe from 2004 to 2013. Finally, Section 4 gives a short conclusion and discussions about the existence of opening questions within this research theme.

2. Data and Methods

As asserted in the Introduction, the principal dispute for the knowledge complexity measurement is the recognition of the technological possibilities. To investigate this phenomenon, complexity economists have improved principles in which they defined them using mathematical methods: we tried to reach this type of complexity through the use of patent data. In particular, we used this data for computing the relatedness measurement between different collection of knowledge (classified by patent classes) and the complexity value of technologies. In this study, for detecting the technological fields of interest, it was helpful the Eurostat Patent Office database. Moreover, the geographical spectrum of the patent was restricted to the European countries (EU28) using the Eurostat database for formulating the SOM analysis.

2.1. The Neural Tool and the Database Used

As previously affirmed, we used, for the geographical spectrum of analysis, a topographic map which is a two-dimensional, non-linear approximation of a potentially high-dimensional data sets where the SOM algorithm is one of the most used.

The principal goal of the SOM is to modify an incoming signal pattern of arbitrary dimension into one-core or two-dimensional discrete maps and to make this transformation, in an adaptive way, in a topologically ordered manner. SOM algorithm sorted out two different stages: the competitive and the cooperative ones. In the first stage, neurons become selectively harmonized to various input patterns (the so called *stimuli*) or classes of input pattern during the course of the competitive learning stage. Consequently, the location of the neurons become ordered and a meaningful coordinate system for the feature is created on the lattice. So, the best-matching neurons are selected, for example, like the *winner*, as result in the Kohonen Network method. In the second stage, the weights of the winner are adjusted as well as those of its immediate lattice neighbours.

Linked to the previous neural approach and under the database construction point of view, we consider two different types of variables. Firstly, the variables that focus on aspects of a country's knowledge production capacity (*capacity dimension*) in terms of:

- Percentage of ICT personnel in total employment and the percentage of ICT sector on GDP are used as a proxy of the ICT development sector;
- Employed share of population with tertiary education (correspond to levels 5 and 6 of ISIC 1992 classification system) describes the persons with ICT education presence in labour force by their employment state;
- Gross Domestic Product per capita as a proxy of the economic development, productivity and socio-economic potential of a country, decisive for country's patent performance.

Secondly, the variables that could be considered as a proxies for country's range of knowledge production activities (*relational dimension*) in terms of:

- High-Tech patents;
- ICT patents;
- Biotechnology patents;
- Nanotechnology patents.

Denoting the technological power of a country's knowledge base.

2.2. The Network Tool: The Knowledge Complexity Index

As expressed in the previous section, it is possible to quantify the knowledge complexity of a country's technological portfolio for a period of time. The KCI used in this paper, is based on the *method of reflections*, developed by Hidalgo and Haussman (2009). In particular, in their work, they showed that the economic complexity of a country is an echo of the product composition of its export pannier. So, their principal idea is the following: the more complex economies produce exclusive goods the more these countries present an exclusive source of

comparative advantage. In this framework, these comparative advantage could be seen as a sort of spatial technological monopoly because of the fact that countries might be emulated by others and, at the same time, the ubiquitous goods present low weights under economic complexity point of view.
Following their style, we have analysed the configuration of the *European country-tech knowledge network,* revealing that country might have a complex technological distribution/combination when it is able to generate knowledge that relatively few others countries could be ready to take off. For the creation of this index, we supposed that European countries are the primary producers of a specific technologies. In this sense the *European country-tech knowledge network* is used as starting point to compute the KCI, in which the technological classes is composed by the country having a relative technological advantage (RTA hereafter) in terms of patenting spread. The *EU country-tech knowledge network* is formulated as a *n*k two mode matrix* (M= $M_{c,i}$) where $M_{c,i}$ represents the presence or not country's RTA, $c = 1,..,n$, in the creation of technological knowledge i ($i = 1,...,k$). More deeply, country, c, has RTA in technology i at time t if the portion of technology i in the country's technological portfolio is higher than the fraction of technology i in the entire EU patent portfolio.
Supporting by the *method of reflections,* KCI is determinate by two set of variables: the *density* of countries and the *ubiquity* of the technology classes, as reported in the equation (1) and equation (2) below

$$KCI_{country} = k_{c,i} = \frac{1}{k_{p,0}} \sum_i M_{p,j} K_{i,n-1} \quad (1)$$

$$KCI_{tech} = k_{i,n} = \frac{1}{k_{i,0}} \sum_i M_{p,j} K_{p,n-1} \quad (2)$$

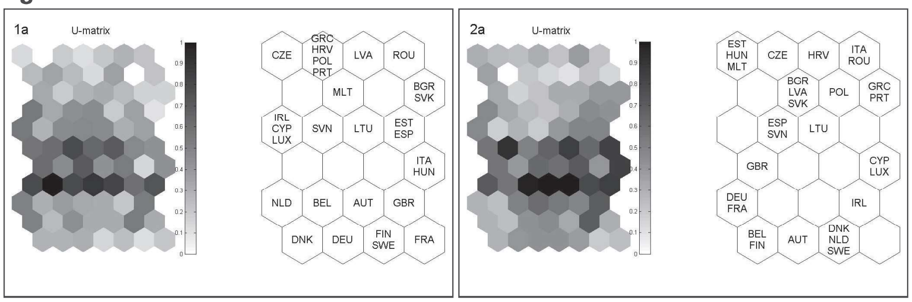
Each additional iteration in $KCI_{country}$ (equation 2) generate a finer-grained estimation of the knowledge complexity of a country using information on the complexity of a technology in which country shows RTA. Furthermore, each additional interaction in KCI_{tech} (equation 2) allows a finer-grained estimation of the knowledge complexity of a technology using information on the complexity of countries that present RTA into the specific technology.

3. The Geography of the European Complex Knowledge

For studying the knowledge complexity of the European countries, we have divided the analysis into two steps: in the first step, we used the SOM approach to provide a short-term analysis of possible presence of spatial relationship between European countries and patent classes. In the second one, we have estimated the knowledge complexity degree through, firstly, the use of the *European country-tech knowledge network*: what emerge from the interconnections between nodes of different types was a network of countries and technologies; and after with the computation and

analysis of KCI related to each European countries. Following, the method of reflections contributes to a more precise measure of the KCI of countries and technologies, where noise and size effects are eliminated because, according to Caldarelli et al. (2012), the iterative method of reflection is an approximation of the fixed-point theorem based on Markov chain analysis.
Concerning the first step, the following Figure 1 exhibits the location of the European countries in 2004 (1a) and after in 2013 (1b). if we focus the attention first on (1a) and after on (1b), there are few, and scarcely significant, movements between the two considered periods.

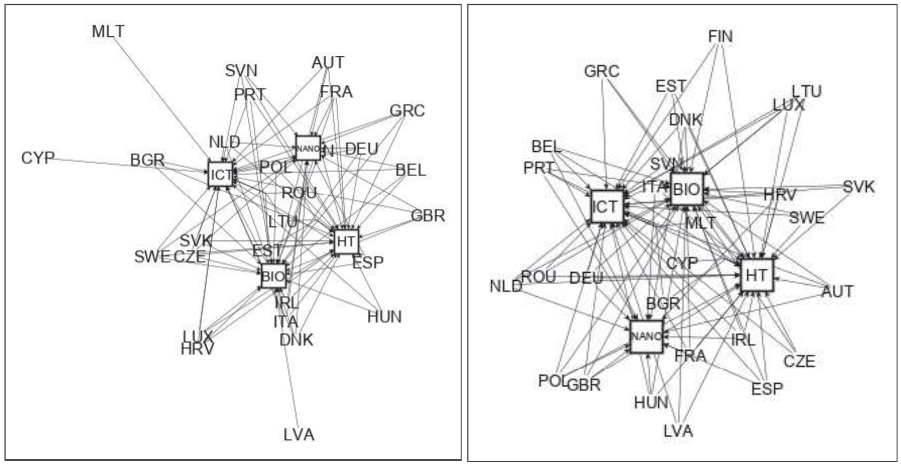
Figure 1: U-Matrix from 2004 to 2013



Source: Authors' elaboration

These few movements provoke a clear separation between the Central and Northern countries and the Mediterranean ones; which remain, at the bottom and upper part of the map respectively. As a result, they originate a notable gap between them and the rest of the sample. Following, it is possible to stress out that the East countries, like Romania Bulgaria, and Slovakia, located at the top of the map, show low values in almost all the considered variables during all the considered period of analysis.
The previous topographic analysis has unveiled interesting spatial patterns across Europe. However, the question that arises is which country knowledge characteristics could drive the observed spatial patterns. At this point, we paid attention on the measurement of the country knowledge complexity embedded in the European knowledge network. So, centring the attention on the second step of the analysis, we started with the implementation of the *European country-tech knowledge network* for the periods 2004 and 2013. This type of network is referred to a *two-mode network* (Borgatti, 2009) where the principal characteristics is the emergence of linkages between nodes of different types, in this specific case between countries and technologies.
In Figure 2, the European countries are symbolized by nodes, instead patents are presented by squared ones (identified with ICT, BIO, HT, and NANO respectively). It follows that the countries positions in the knowledge space reveal the technological classes in which they display relative technological advantages and the density of their patents across these classes. Indeed the spatial connectivity affects a country network position due to the spillover mechanisms resulting from economic dependencies, agglomeration dynamics or core-periphery structures (Feldermann and Kogler, 2010).

Figure 2: The structure of the *European country-tech knowledge network* from 2004 to 2013.



Source: Authors' computation and visualization

As it is possible to stress out from the above Figure 2, there are rare movements between the two periods of analysis, as profiled during the first stage of our analysis. For instance, it is possible to see a specialization of some countries, especially the Eastern Block in Biotechnologies. More diversified countries instead, occupy the periphery of the knowledge space, in which links between Nanotech nodes are not particularly dense.

Being a simple visual representation, it does not provide a knowledge complexity measurement so, for that reason, it is necessary to provide a statistical analysis using KCI.

Table 1: The Knowledge Complexity Index (years: 2004 - 2012)

	2004	2013		2004	2013		2004	2013
BEL	100.00	100.00	HRV	100.00	100.00	POL	97.30	99.97
BGR	0.00	0.00	ITA	91.37	0.73	PRT	100.00	100.00
CZE	0.00	0.00	CYP	0.00	0.00	ROU	84.06	0.00
DNK	100.00	100.00	LVA	100.00	100.00	SVN	64.87	99.99
DEU	50.00	0.00	LTU	0.00	100.00	SVK	92.03	100.00
EST	0.00	0.00	LUX	28.09	34.49	FIN	0.00	0.00
IRL	0.00	100.00	HUN	78.09	35.22	SWE	66.54	6.77
GRC	100.00	0.00	MLT	0.00	34.49	GBR	100.00	100.00
ESP	54.31	100.00	NDL	92.82	99.92			
FRA	0.00	100.00	AUT	0.00	0.00	EU28	4.00	4.00

Source: Authors' computation

As it is possible to stress out from the previous Table 1, the KCI for the European countries is quite homogeneous over the considered period. In 2004, knowledge complexity is moderately high (60<KCI<80) in Romania and Slovenia because they presented strong positive innovation performance trend due to their very low starting innovation proxies values. In comparison, in 2013, their KCI values diverged, from 84.60 to 0.00 for Romania and from 64.87 to 99.99 for Slovenia. This divergence could be explained as follows: in 2004 both countries presented quite similar innovation performance values together with Portugal, Latvia, Cyprus, Hungary and Slovakia. Instead, in 2013, most of the previous countries had managed to improve group membership from the catching-up group to Modest and Moderate Innovators. Slovenia has dropped from the catching-up group and is now a Innovator follower. Romania is still in the same performance group as in 2004. Knowledge complexity is high (KCI>70), for example, in Denmark, United Kingdom and Belgium. These countries tend to develop a number of technologies that could only be replicate in a small number of other European countries. In conclusion, it is also clear from the Table 1, that the leading countries of complex knowledge production are concentrated in few countries, identified for their innovative performance, as Innovation Leaders and Innovation Followers respectively.

4. Conclusions

In this paper, we have introduced a practical application of the method of reflections to the European patent data, describing the spatial patterns and transformation of the complexity knowledge, originated in the European countries from 2004 to 2013. The result of our analysis is the presence of a static geography situation, where only a few European countries, especially the Northern ones, are producing the most complex new technologies. Under this view, the previous considerations are important for the development and implementation of the country's innovation policy. But, speaking in complex knowledge terms, innovation guidelines might be considered a useful instrument for the growing of the related areas but also in that technologies which are more complex than the actual ones.

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