Development of a new indicator to rank the geographical distribution of the European knowledge base

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Resumen: Geography and spatial aspects have been both highlighted as important elements for the knowledge base, which is acquired and usually disseminated through social interaction and accumulation processes on previous knowledge. Furthermore, the advance in knowledge leads to innovation, understood as the development of new ideas that create value for firms and allow them to build a regional competitive advantage. While the European Union has places a considerable emphasis on the confection of indices measuring phases or aspects of innovation (Innovation Union Scoreboard and Regional Innovation Scoreboard) and competitiveness (Union Competitiveness Report and Regional Competitiveness Index), studies on the configuration of the base of scientific and technical knowledge in Europe have been very scarce. Therefore, this paper addresses the measurement of the regional knowledge base - understood as the availability to access to the specialised sticky specific knowledge resources of a territory, which normally are tacit - in Europe through a new and robust indicator. This measure allows creating a ranking of the European regions on the basis of their degree of knowledge base profiles.

Key words: knowledge base, measurement, evolution, index, Europe.

JEL codes: D83, R11, O18, O52.

INTRODUCTION

In a knowledge-based economy, knowledge resources have become strategic assets that are crucial to the existence of competitive advantage (Asheim and Coenen, 2005; Asheim, Boschma and Cooke, 2011; Cooke and Leydesdorff, 2006; Kauffeld-Monz and Fritsch, 2013) at both the micro and macro levels (Schiuma and Lerro 2008). However, the literature has noted that there is still a need for a better analysis of the measurement of the knowledge base, particularly at the regional level (Godin 2006). For this reason, an investigation into the measurement and evolution of the knowledge base in the European regions appears to be of great relevance.

The advancement of knowledge leads to innovation, which is understood as the development of new ideas that create value for firms (Asheim, Gertler, 2005; Tödtling and Trippl, 2012) and allow them to build a regional competitive advantage (Caniëls and Romijn, 2006). Therefore, continued innovation requires a well-planned knowledge management system to enable the company to achieve excellence in knowledge creation. Thus, innovation and knowledge creation are distinct concepts – although closely associated – and have a complex relationship with each other (Popadiuk and Choo, 2006).

Furthermore, geography and spatial aspects have been highlighted as important elements for the configuration of the knowledge base (Kauffeld-Monz and Fritsch, 2013). In this line, prior studies have stressed the positive influence that knowledge concentration has on the development of robust economic activity in certain areas (Alonso-Villar and Del Río, 2013; Archibugi and Coco, 2003; Asheim, 2012; Asheim, Boschma and Cooke, 2011; Asheim and Gertler, 2005; Tödtling and Trippl, 2005).

Some illustrative examples of the importance given to the knowledge economy for economic development in the new era relies on the profusion of studies that attempt to measure the knowledge base from several points of view. Therefore, some of them have adopted the triple helix – even later expanded to an N-tuple of helices – approach to measure the knowledge base in terms of the relationships between technology, organization, and territory (Leydersdorff, 2012; Leydersdorff et al., 2006, 2014). Others have followed the building of indices and rankings by country and region with regard to the knowledge base, innovation and competitiveness. In this latter case, on the one hand, among the indices addressing the measurement of the knowledge base by countries, some of the most prominent ones include the Knowledge Economy Index published by the World Bank and the OECD Science, Technology and Industry Scoreboard. On the other hand, there have also been influential indices on innovation – such as the Global Innovation Index published by World Intellectual Property Organization (WIPO) and on competitiveness – for instance, the Global Competitiveness Report published by the World Economic Forum (WEF). In the case of the European Union, emphasis has been placed on the variety of indices measuring the phases or aspects of innovation (Innovation Union Scoreboard and Regional Innovation Scoreboard) and competitiveness (Union Competitiveness Report and Regional Competitiveness Index) both at national and regional levels. However, studies on the configuration of the base of scientific and technical knowledge in Europe have been very scarce.

This paper adopts a different approach to fill this gap in the literature by addressing the measurement of the regional knowledge base, understood as the availability to access to the specialized sticky specific knowledge resources, which are normally tacit, of a territory in Europe through a synthetic index. We contend that this paper may contribute to the existing literature in different ways. First, our analysis sheds light on the main components that drive the knowledge base in Europe, taking into account a wide variety of variables. This perspective may be of great relevance considering that one of the main priorities of the Europe 2020 strategy is the achievement of smart growth through the development of a knowledge-based economy (noting that the role of regions may be important). Second, this study provides a dynamic approach by investigating a set of thirteen annual series of data to elaborate a series of the evolution of a synthetic index and its partial components. This enriches previous works, mainly centered in either a single period or a set of very few years, and it proves to be a useful tool for the design of efficient regional policies.

To meet this goal, this paper is divided into four sections following this introduction. In the second section, we revise the importance of geographical proximity in the formation of the knowledge base that gives a competitive advantage to organizations and countries. In the third section, we provide the estimation of an index that can be applied to European regions to establish a ranking and classification of a number of different features between European regions. In the fourth section, we analyze the results. Finally, in the last section, we summarize the main conclusions and limitations.

PROXIMITY AND REGIONAL KNOWLEDGE BASE

Dimensions of the proximity

The knowledge base is acquired and usually disseminated through social interaction and accumulation processes on previous knowledge (Asheim, 2012; Caniëls and Romijn, 2006; Kauffeld-Monz and Fritsch, 2013; Rutten and Boekema, 2012). Given that it arises from the combination of existing ideas, capabilities, resources, etc., the greater the variety of these factors in a given system, the greater the scope to be combined in different ways and the greater the possibility of generating more complex and sophisticated innovations (knowledge) (Fagerberg 2005). Therefore, as basic conditions for the generation of knowledge, we can cite several aspects that are closely linked to proximity, such as accessibility to a broad base of knowledge (access to resources), the establishment of relationships among agents having knowledge, a favorable attitude to its acquisition (absorption capacity), and an institutional framework that allows it.

The importance of proximity in the formation of knowledge that is accessible to organizations has primarily been manifested in the distinction between two categories of knowledge: tacit and codified.[1] While the generation of new knowledge requires the use of both types and both are virtually indivisible, previous studies have pointed to tacit knowledge as the most important base in the creation of innovation-based value (Asheim and Gertler, 2005). Given its nature, the generation and transmission of tacit knowledge requires proximity through different dimensions (Boschma, 2005).

However, the role given to proximity in knowledge formation has been controversial. In this regard, previous studies have indicated that the widespread use of geographical proximity as the main concept may have masked dimensions that are not strictly spatial, such as cognitive, social, organizational, and institutional dimensions (Boschma, 2005; Hassink and Klaerding, 2012; Knoben and Oerlemans, 2006, 2012; Rutten and Boekema, 2012; Rallet and Torre, 1999; Torre and Rallet, 2005).

Boschma (2005) provides an interesting framework with which to analyze each dimension of proximity. Thus, cognitive proximity is manifested in the sharing of languages, codes and knowledge of the same or related scientific field. Organizational proximity refers to the ability to coordinate the exchange of information in this case, which belongs to a variety of stakeholders both within and between organizations. Social proximity is expressed through the networks of social relations based on mutual trust that results from a history of successful collaboration and informal interaction. Meanwhile, institutional proximity implies the adoption of rules and conventions that emanate from a shared institutional environment, which governs the relations among different agents of knowledge and the appropriation of income from inventions. Therefore, the probability of the generation and transmission of tacit knowledge is largely based on the main elements of so-called social capital (see Echebarria and Barrutia (2013) for further review of this concept): institutional capital, relational capital, and mutual trust (Malecki, 2012). Finally, geographical proximity facilitates 'face-to-face,' informal, spontaneous and repeated interactions, for which physical distance plays a crucial role, among partners who already share some of the basics mentioned above. Thus, “the establishment of a social climate of mutual trust promotes the local flow of tacit knowledge” (Asheim and Gertler, 2005: p. 293) and “allows actors make commitments and reduce the incentive problems in uncertain environments” (Healy and Morgan, 2012: p. 1046). These different dimensions of proximity can be complementary and substitutive to each other, with cognitive proximity being the only necessary condition (Boschma, 2005).

Previous works have provided a predominant focus on the regional geographic dimension (e.g., Rutten and Boekema, 2012), reaching no unanimous conclusions. On the one hand, a stream of literature has emphasized the importance of the concept of a 'learning region' (Florida, 1995) as the core of analysis in which mutual trust becomes very important. This trust would therefore be generated in a region by sharing the norms and values promoted through a series of institutions derived from the local governance system linked to a specific territory, and such trust would have a very significant impact on the production and dissemination of knowledge (Asheim, 2012; Healy and Morgan, 2012). Furthermore, another stream of literature criticizing 'spatial fetishism' has stated that actors learn, not regions (Hassink and Klaerding, 2012). This perspective assumes that people learn, and, in any case, the organizations – firms, universities, and laboratories, among others – have knowledge and can accumulate it. Taking this view, the concept of a 'learning region' would be essentially regulatory and overlap with other concepts such as: clusters, industrial districts and regional innovation systems, among others. However, regardless of the current literature, all studies agree on the key role played by the geographical dimension of knowledge accumulation (Rutten and Boekema, 2012).

Human resources and sources of knowledge in the formation of the regional knowledge base

The main resources for the formation of the regional knowledge base can be divided into resources that are internal and external to organizations (Rutten and Boekema, 2012). Additionally, in this second subgroup, the territorial environment (local / regional sources) and external sources are also included. Beyond the spatial perspective, it is possible to make a distinction between human capital and other sources of knowledge.

Human capital is usually acquired through the education system and learning and experience in the workplace. The importance of the proximity to the availability of specific and specialized human capital is related to their degree of geographical mobility, something that is greatly affected by professional and other factors. Among the first group, we can cite the existence in the city of a broad professional community and 'other sources of knowledge' to enable these workers to maintain and advance their knowledge. Furthermore, the availability of a favorable social and cultural environment may increase their ties and develop their roots in the territory considered.

The sources that achieve knowledge can be grouped in many ways. Numerous works such as the study by Doloreux et al. (2008) have noted that there are at least three categories that can encompass the different resources that facilitate the acquisition of knowledge. First, there is knowledge that can be obtained through various institutions dedicated to promoting it (Rodríguez-Pose, 2013), which in the case of high and specialized knowledge include universities, laboratories, and research institutes, among others; these institutions are called knowledge infrastructures (Doloreux et al. 2008). Some organizations, usually large companies that have their own laboratories or research institutes, can accommodate any type of these institutions or establish some type of relationship with them.

Within this first category of the classification of the generators of knowledge, we can consider both the dissemination of tacit and explicit knowledge. In the former case, its effective transmission implies, as already mentioned, a close relationship between the company staff and the members of the scientific and research community, either within the company or externally.

Second, there is knowledge that is primarily obtained through market relationships with customers, competitors, suppliers and consulting firms, through mergers/acquisitions, or via agreements/alliances. In some of these cases, it is essential that there is a high degree of trust that facilitates the exchange of basic information to attain knowledge. The evaluation of the sources of knowledge that can be transmitted through market relations could lead to value network system of relationships established by local businesses with each other within the territory and with the outside, especially with regard to the acquisition of knowledge that can be strategic for the innovation and competitiveness of local businesses. The data needed to estimate this dimension should come primarily from the companies themselves, and they should distinguish between strictly local relations and those generated from the outside.

Third, there are overall resources of information derived from meetings, conferences, trade shows, newspapers, business associations, and the Internet, among others. In principle, access to these sources is open, and precisely the degree of broad geographic accessibility implies that these resources are not a source of knowledge that generates a specific local advantage.

The role of each of these sources and their importance in the formation of the regional knowledge base may vary by the area of activity, location, and stage of the industrial cycle, among other factors.

Different types of regional knowledge bases

Considering the importance attached to each of these types of knowledge sources , the literature has distinguished three categories of knowledge bases: analytical, synthetic and symbolic (Asheim, 2012; Asheim, Boschma and Cooke, 2011, Asheim and Coenen, 2006). Table 1 summarizes the main features that define each of these knowledge bases.

Table 1. Differentiated knowledge bases: a typology.

Analytical (science based)	Synthetic (engineering based)	Symbolic (arts based)
Developing new knowledge about natural systems by applying scientific laws; know-why	Applying or combining existing knowledge in new ways; know-how	Creating meaning, desire, aesthetic qualities, affect, intangibles, symbols, images; know-who
Scientific knowledge, models, deductive	Problem-solving, custom production, inductive	Creative process
Collaboration within and between research units	Interactive learning with customers and suppliers	Experimentation in studios and project teams
Strong codified knowledge content, highly abstract, universal	Partially codified knowledge, strong tacit component, more context specific	Importance of interpretation, creativity, cultural knowledge, sign values; implies strong context specificity
Meaning relatively constant between places	Meaning varies substantially between	Meaning highly variable between place, class and

	places	gender
Drug development	Mechanical engineering	Cultural production, design, brands

First, the analytical knowledge base is generated at industrial sites in which scientific knowledge is very important and where knowledge creation is often based on rational cognitive processes or formal models (e.g., biotechnology and nanotechnology) (Vale and Carvalho, 2013). In such an environment, the relevant activities for the development of products and processes consist of both basic and applied research. Companies usually not only have their own R&D departments, but they also base their innovations on research results from universities and other research organizations. The industry-university relationships and the respective networks are therefore important and more frequent than in other types of knowledge bases. The inputs and outputs of knowledge are more often encoded than in other types of bases. This does not imply that tacit knowledge is irrelevant because both codified and tacit knowledge are needed in the process of knowledge creation and innovation.

Activities require specific skills and abilities; in particular, the presence of analytical skills, abstraction, and theory construction is needed more frequently than in other types of knowledge. Consequently, it is required that the labor force has solid research experience and university education.

Knowledge creation in the form of scientific discoveries and technical inventions that can lead to patents and manufacturing licenses is more important. The application of knowledge is reflected in the form of new products or processes, and more radical innovations are observed. A major route of knowledge application is the generation of new companies and spin-offs that have been formed from radical innovation (European Commission, 2006).

Secondly, the synthetic knowledge base would occur at industrial sites where innovation takes place mainly through the application of existing knowledge or through new combinations of knowledge. This often occurs in response to the need to solve specific problems arising from the interaction with customers and suppliers (e.g., advanced and specialized industrial machinery, engineering, shipbuilding, etc.). Thus, the products are often produced in small series or are unique products.

Overall, R&D is less important, taking the form of applied research, but most often the form of the development of products or processes. The industry-university relationships are relevant but are more focused on the field of applied research and development than on basic research.

Knowledge is most often created through an inductive process rather than a deductive process or through practical work. Moreover, knowledge is incorporated into the respective technical solutions or the work of engineers and is only partially encrypted. Thus, tacit knowledge is more relevant in this knowledge base because knowledge is often the experience gained in the workplace or acquired through learning (learning by doing, using and interacting). It provides a more concrete know-how, craft and practical skills in the process of production and circulation provided by polytechnical schools and professionals or by learning in the workplace.

The innovation process is often geared toward the efficiency and safety of new solutions or the practical usefulness and usability of the products from the perspective of customers. This generally leads to a form of incremental innovation that is rather dominated by the modification of existing products and processes. Thus, innovations are less groundbreaking routines and organizations, many of which take place in existing firms, while spin-offs are less common (European Commission, 2006).

Third, the symbolic knowledge base is related to the aesthetic attributes of products, creating designs and images, and the economic use of various forms of cultural devices. This type of knowledge has become increasingly important and is manifested in the development of cultural industries, such as media (film, publishing and music), advertising, design, fashion, etc. These industries are intensive in innovation and design, as a crucial part of their work is dedicated to the creation of new ideas and images and less to physical production process.

In these industries, the input is aesthetic rather than cognitive. This often demands more specialized skills in symbolic interpretation than in mere information processing.

Symptomatically, trucked knowledge is incorporated and transmitted in aesthetic symbols, images, designs, artifacts, sounds and narratives. It is closely linked to a deeper understanding of the habits, norms and 'everyday culture' of specific social groups, and it therefore has a strong tacit component. The acquisition of essential creative, imaginative and interpretive skills is less tied to formal qualifications and university degrees than to practice at various stages of the creative process. It is important to acquire not only know-how but also know-who, i.e., the knowledge of potential partners with complementary expertise.

Finally, an essential aspect is that production is organized in temporary projects (such as cinema). More generally, the project provides an organizational environment in which the diverse spectrum of professional cultures ranging from the art world to the commercial world of business services is collected for a limited period of time. The projects on the basis of symbolic knowledge are not necessarily directed to bind or minimize such diversity in a direct way. They can also be referred to as settings for productive tensions and conflicts that unleash creative innovation.

This paper focuses on both the sources of knowledge internal and external to the companies.

INDEX OF A REGIONAL KNOWLEDGE BASE

Some antecedents

The relevance achieved by the 'knowledge-based economy' in both the theoretical and applied dimensions has driven the development of indices that, thanks to the availability of information at the national level, allow the establishment of rankings of countries. Some other studies have adopted a triple-helix – even later expanded to an N-tuple of helices – approach to measure the knowledge base in terms of the relations between technology, organization, and territory (Leydersdorff, 2012; Leydersdorff et al., 2006, 2014).

However, from the sub-national or regional perspective, the availability of data and official works in this regard has been much lower. To illustrate this, we can cite the case of the European Union reports on innovation (Regional Innovation Scoreboard) and competitiveness (Regional Competitiveness Index), which are both closely related to the formation of knowledge but correspond to different stages of the process.

Methodology of a synthetic index for the regional knowledge base

The construction of a synthetic index that brings together the main knowledge resources that exist in a territory implies several types of difficulties and choices. First, there are issues related to the selection of data to be used (database), to the type of territorial unit to be studied (region, province, county, municipality, etc.), the time period to be taken as the basis of the index, and the variables that make up the index.

As for the processing of data, various types of choices are also raised: standardizing the variables if they are represented in different units or magnitudes, determining their weights, and classifying the results.

To develop this synthetic knowledge base index (KBI), which aims to reflect the knowledge base of each territory, we have chosen a weighted arithmetic mean of the different component variables:

$$\mathbf{KBI = \Sigma_i\, p_i\, x_i.}$$

$\mathbf{p_i}$: weights of the **i** variable.

$\mathbf{x_i}$: values of the **i** variable.

In turn, it is possible to split up the index in different subindices that explain the positions of each region within the various knowledge resources considered.

Selection of data and variables

Major figures published by Eurostat – the database used in this work – are offered according to the different variables considered at several territorial levels. The greatest variety is published for the subnational level NUTS I, while for the NUTS III level, information hardly exists. Therefore, we chose the level NUTS II.

The analyzed period begins in 2000, from which there is a sufficient amount of representative data for European regions on the formation of the knowledge bases that stimulate the generation of advanced, specialized and specific knowledge that organizations can use to innovate. The change in methodology in some variables – such as employment in high-tech activities – has led to the choice of 2008 as the basis for the series of indices from that date backward and forward for the development of many statistics in Europe.

The estimation of the sources of knowledge internal to the company was made through the variables related to the research effort of companies: R&D and researchers relativized in relation to GDP and the active population, respectively.

As noted above, the sources of knowledge outside the company and, in this paper, of a domestic nature of a territory have been divided into human resources, knowledge infrastructure, sources from the market, and general sources.

The estimation of human resources has relied on Eurostat data on Human Resources in Science and Technology (HRST), which considers two criteria, education (HRSTEd) and occupation (HRSTOc), which essentially refer to workers with the formation equivalent to tertiary education. In both cases, the data were relativized for the active population.

Access to knowledge infrastructure in an area is estimated using two types of institutions: government (Gov) and higher education (HE) institutions, which are essentially universities. For each of them, we have considered the effort made, taking into account both the expenditure and staff engaged in research, as in businesses (Buss).

The sources of knowledge derived from market relations have been estimated from the perspective of suppliers, customers, consultants, and even local competitors. To that aim, we have used as an approximation the relative data on employment in knowledge-intensive business services (KIBS), particularly high-technology (HTKIS) and market services (MKIS), which can both be providers of knowledge-intensive services and constitute the main forms used by consulting firms. The knowledge demand through the market can be estimated through the presence of medium-high and high technological intensity manufacturing (HTM). Although it is considered that the flow of knowledge in both types of activities is not performed in one direction, for the sake of clarity, we have simplified it because the above directions can dominate. To reflect their importance in the territory, they have been relativized in relation to the total active population.

Finally, general knowledge sources have been approached through the access and use of the Internet. We will not consider the Internet as a result of the easy access to information from almost everywhere and because it is not a specific source of knowledge belonging to concrete territories.

The poor quality and lack of data in many cases to an extent that is more than desired has forced to make an imputation process using the criteria of the nearest available data in time, in space (NUTS I or, where appropriate, the state to which it belongs), and/or a combination of both.

Weights calculation

The decision concerning the weighting of the relative importance of different variables has often been based on *ad hoc* decisions. Thus, some works have used subjective criteria, either considering that each subindex has the same importance in the composite index, or assigning a certain weight to each subindex at its discretion. However, these subjective criteria do not always have a selfless character and lead to the optimization the results of a particular country or region (Grupp and Moguee, 2004). In the knowledge base synthetic index proposed in this paper, we apply a method that is based on the results of a factor analysis (FA) to overcome this subjectivity of previous works, thus contributing to somehow alleviating the discretional nature of previous empirical studies.

The relative weight of each of the variables was calculated from the results of FA. The idea is to weight each of the variables in terms of their real participation in the knowledge base considering statistical criteria and not from a random perspective or based on purely theoretical considerations that may have a subjective bias perspective.

For the base year, these weights in the final index will be determined by the variability of the factor relative to the total variability. Thus, the variables and factors with greater variability have a greater weight than those variables that reflect a more homogeneous distribution among regions.

With respect to the weight of the variables, the weighting within each partial index is calculated from the eigenvector matrix. The relative weight is calculated as a product of this matrix by the vector of eigenvalues, finally dividing the results obtained by the total so that the sum of the weights is equal to unity.

Classification of regions

Finally, the classification of the regions was performed using a cluster analysis techniques (CA) and particularly the k-means technique[2] because it has not established any number of categories a priori. The choice of the number of groups is performed depending on the evolution of the sum of squared errors and the robustness of the results.

RESULTS

Table A1 (in the Appendix) gathers the correlations among variables. Overall, it points to a strong relationship between expenditures in R&D and the number of researchers for every institutional category[3] and between employment in HTKIS and MKIS. The relationship between HRSTCore and HRSTEd has also been revealed as very high and between HTM and HRSTOc. Then, our analysis takes into account six components of the synthetic KBI: Buss-Business effort in research (expenditure in R$D and researchers in R$D), Gov (Governmental effort), HE (Higher Education effort), HRST (Core and Education), HTM (employment in High-Tech and Medium-High-Tech Man, and HRST Occupation), and KIBS (employment in HTKIS and MKIS).[4]

Furthermore, Table 2 shows the weighting for each variable obtained through the application of FA. The biggest weighting has been observed for variables related to research, highlighting Business Research within them due to the greatest variations in their values. Technology and Knowledge Intensive Sectors (TKIS) have followed in importance. Finally, regional differences in HRST have been of lesser importance.

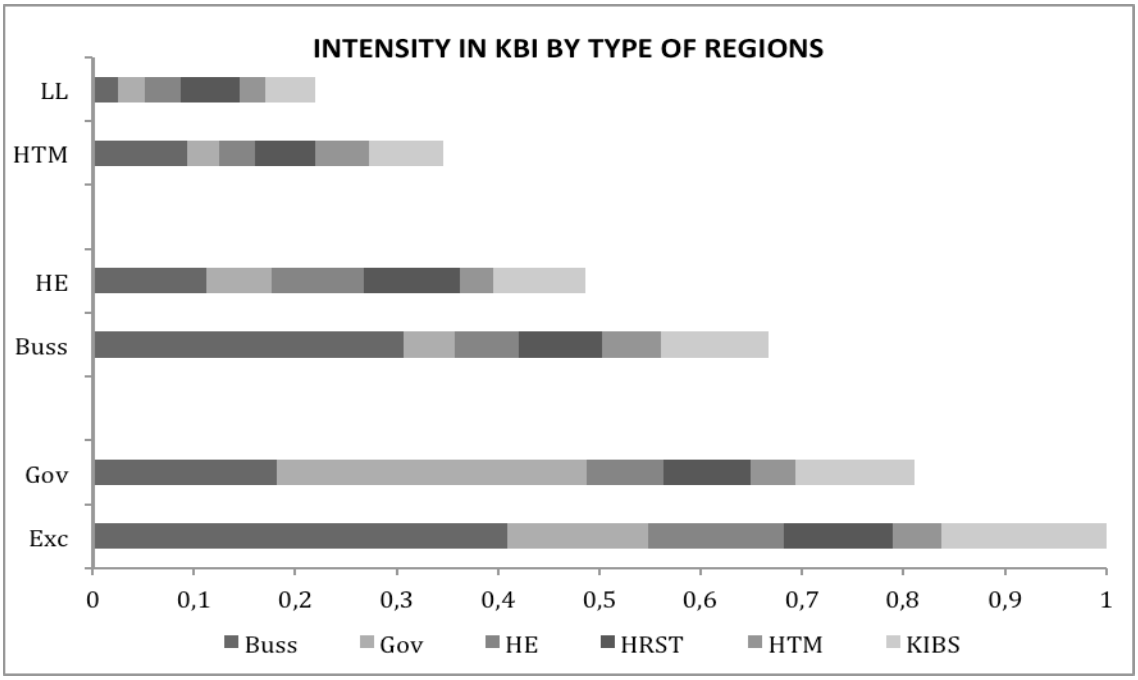
Table 2. Variables weighting

	2008
Ebuss: R & D Expenditure Business Sector (% GDP)	0,15042
Egov: R & D Expenditure Government Sector (% GDP)	0,09169
EHE: R & D Expenditure Higher Education Sector (% GDP)	0,07634

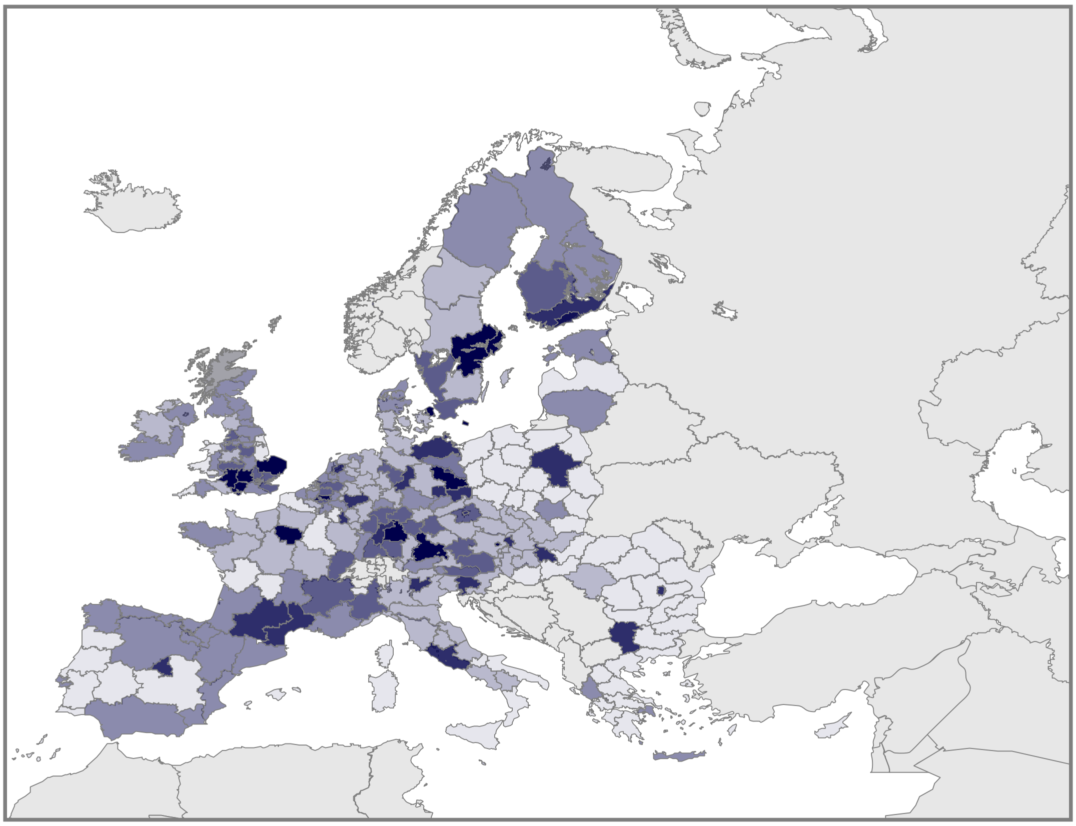
Rbuss: R & D Researchers Business Sector (% EAP)	0,15109
Rgov: R & D Researchers Government Sector (% EAP)	0,07509
RHE: R & D Researchers Higher Education Sector (% EAP)	0,05432
HRSTCore: Human Resources in Science and Technology – Core (% EAP)	0,08312
HRSTEd: Human Resources in Science and Technology – Education (% EAP)	0,06614
HRSTOc: Human Resources in Science and Technology – Occupation (% EAP)	0,03370
HTM: Employment in High and medium high-technology manufacturing (% EAP)	0,04516
HTKIS: Employment in Knowledge-intensive high-technology services (% EAP)	0,09246
MKIS: Employment in Knowledge-intensive market services (% EAP)	0,08047
Buss: Business researching effort	0,30151
Gov: Government researching effort	0,16678
HE: Higher Education researching effort	0,13067
HRST: Human Resources in Science and Technology	0,14926
HTM: HTM & HRST Occupation	0,07886
KIBS: HTKIS & MKIS	0,17293

The application of CA through a K-mean method to standardized and weighted data have shaped six groups of European regions[5] with a great homogeneity within them and a great difference among them. These groups have been classified into three categories: above, below and around the EU mean. The first category includes two groups that were labeled as ‘excellence’ and driven by the ‘government’ because of having achieved high values in the synthetic KBI and their components in general or mainly in the Gov KBI. Figure 1 shows the relative intensity of every KBI by the type of region. Conversely, two of these six groups obtained the lowest values in the KBI and have been named as the ‘lowest level’ (LL) and driven by the ‘HTA’ (High-Tech Activities) due to the higher relative values reached in the last group. Finally, the two remaining groups have obtained values around the EU-27 mean and have been named as intensive in ‘Business research’ (Buss) and the ‘Higher Education Sector’ (HE) because of their more relevant characteristics. Map 1 shows the regional types.

Figure 1. Intensity in KBI


INTENSITY IN KBI BY TYPE OF REGIONS
LL
HTM
HE
Buss
Gov
Exc
0
0,1
0,2
0,3
0,4
0,5
0,6
0,7
0,8
0,9
1
Buss
Gov
HE
HRST
HTM
KIBS

Map 1



Spatial patterns of knowledge base indices

The establishment of typologies is useful to highlight the strengths and weaknesses of every region in the formation of their knowledge base as well as to build references to guide the strategies of a regional technological policy that is smarter and more efficient.

This analysis shows a landscape that points to a complex center-periphery pattern made up of several subpatterns in which uniform and polarized morphologies (OECD, 2011) may coexist. Overall, regions hosting national capitals have reached higher values in KBI, while the remaining regions of their own States have obtained much lower values in KB, and the differences between the first ones and the second ones have been very high. Because of that, in some countries – Austria, Czech Republic, Denmark, France and Slovakia – internal regional differences in KBI have been very important.

The highest values in KBI have been reached in the 'excellence' and 'government' regions. In the first group, the intensity of business research has been the highest and very much above the remaining regions and the remaining KBI in this group. Then, the KBI should be wide and deep, and they may display important competitive (constructed) local advantages and ease with which to grow and generate employment. 'Knowledge hubs' (OECD, 2011) and 'leading innovation regions' (European Commission, 2012) would be located in this space, and they would enjoy favorable atmospheres in which to generate, absorb and diffuse knowledge. This space might contain a smart combination of high levels of synthetic, analytic and symbolic knowledge (Asheim, 2012; Asheim, Boschma and Cooke, 2011, Asheim and Coenen, 2006); nevertheless, the main challenge for the future is to maintain employment in HTA.

The other group in this category has been characterized by a great relative importance of governmental research – the corresponding index has exceeded three and four times the respective European mean – and many national capitals have been included in it (European Commission, 2006). This may be the reason for hosting a great deal of public research infrastructure. This group may be divided into two additional groups. The first group has developed a larger amount of business research. In the second group, the role of HTM has been very relevant. The first group is more balanced. The main challenge for this group is to boost business research to balance the differences in government research.

Table 3 shows that mainly research in business and government, wealth and employment in KIBS has been concentrated in these two regions with respect to the values reached in terms of area and population.

Table 3. Regional knowledge shares by regional category

				RD expenditure			Researchers		
	Number	Area	GDP	Buss	Gov	H E	Buss	Gov	H E
Excellence	13	2,83	14,58	28,89	22,32	21,88	27,72	14,46	17,93
Government	24	7,69	11,29	12,72	34,99	13,28	13,58	41,28	12,94
Business	29	9,70	13,36	25,12	9,55	12,94	20,38	6,70	9,75
H Education	62	28,09	26,56	16,75	20,05	29,64	19,92	21,11	34,29
HT Manu	67	22,28	24,12	14,71	9,89	15,90	14,48	9,82	11,83
Lowest levels	69	29,41	10,08	1,81	3,19	6,36	3,92	6,64	13,25
Total	264	100	100	100	100	100	100	100	100

					HRST		Employment		
	Population	EPA	Emp	Core	Educ	Occup	HT Manu	HT KIS	M KIS
Excellence	7,94	8,61	8,91	7,18	7,47	7,08	10,23	17,70	13,81
Government	11,05	11,36	11,54	11,37	10,02	9,87	10,90	19,35	13,98
Business	10,73	11,10	11,54	12,03	12,80	12,85	16,60	11,66	12,25
H Education	24,86	25,28	25,07	27,41	33,91	33,28	17,89	25,53	26,12
HT Manu	23,61	23,14	23,40	21,65	18,62	18,80	31,59	16,74	21,40
Lowest levels	21,81	20,52	19,55	20,37	17,18	18,13	12,79	9,02	12,44
Total	100	100	100	100	100	100	100	100	100

To the contrary, the group of regions reaching the lowest values in the KBI has overall been located in peripheral areas. This space has been characterized by the ‘lowest level’ (LL) of research, highlighting Buss KBI and Gov KBI. Obviously, these regions should exert a great deal of effort to catch up with the remaining regions. Then, many of these regions have been assisted by structural founding whose influence may have played a role as well.

A slightly better position than the previous group has been reached by the 'HTA' regions, which have shown higher values in this index. This may qualify the group as knowledge-driven by markets, and it might point to a nearly synthetic KB; however, the lower effort in business and government research shows their main weaknesses, which in turn reflect future areas of improvement.

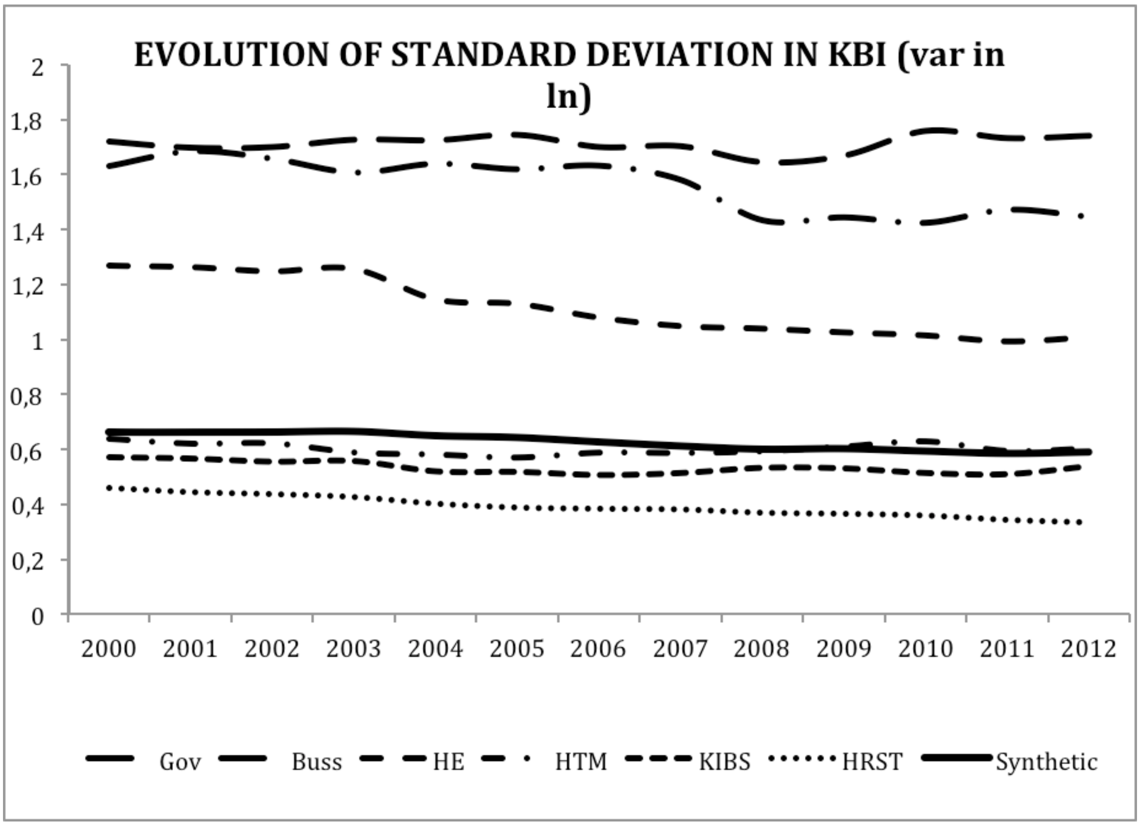
Two remaining groups of regions have placed their KBI around the EU mean. One of them has been characterized by higher values in HE KBI and HRST KBI. Then, their knowledge bases may have been analytical. In the other one, higher values in Buss KBI have been its main asset; therefore, their knowledge bases might be labeled as synthetic, but these regions have suffered from much lower values in HE KBI and Gov KBI, showing their main weakness. In both, the main challenge is to balance the research effort made by different institutions, boosting the worst-positioned among them.

Then, this index has pointed to deep differences in knowledge base in EU regions when economic growth and employment generation depend on creating intangible assets based on knowledge performance. For the EU states, knowledge and innovation are the main drivers of the future. This requires an improvement in the quality of education, consolidating the results of research, promoting the innovation and transfer of knowledge in the EU, exploiting the information and communication technologies (ICT) to the maximum and guaranteeing that innovative ideas may give rise to new products and services to generate growth and quality jobs that help to face the challenges derived by the social changes occurring in Europe and around the world (European Commission, 2010).

Spatial allocation of knowledge base indices

The greatest regional differences in KBI, reported by the standard deviation (in ln) as seen in Figure 2, have been observed in research indices: the highest in government research KBI and the second-highest in business research KBI. Conversely, the smallest territorial disparities have been found in HRST KBI.

Figure 2. Evolution of standard deviation in KBI



Every index has shown a different pattern of localization[7]. Then, the regional allocation of government research has displayed a high polarization in the EU-27. On the one hand, it has been concentrated in regions hosting national capitals or in areas that have been special objects of national policies as is the case of some Eastern German regions. On the other hand, the lowest levels of government research have been situated in the remaining regions that are not national capitals in several countries or even in whole countries. This may point to some explanations based on national factors.

Overall, the spatial allocation of business research has also been very concentrated in areas with high levels of wealth in the EU-27. Therefore, there has been a strong relation between the regional distribution of the synthetic KBI and that of the business KBI. A high level of spatial concentration has also been observed in the HTM KBI around the geographical center of the EU. However, the regional allocation of KIBS KBI seems to exhibit a morphology of multiple geographical centers and peripheries in the level of every country in general.

Spatial differences in HRST KBI have been less visible; nevertheless, some institutional aspects may have yielded some disparities within countries between national capitals and the remaining regions. A similar pattern holds in terms of HE KBI.

Regional KBI evolution

In relation to the spatial evolution of KBI, synthetic KBI for the EU-27 has increased continuously since 2000. Hence, we could state that knowledge has advanced in Europe. In this progress, HRST KBI and HE KBI can be highlighted for their ascension above the remaining KBIs. Conversely, HTM KBI has declined, while KIBS KBI and Gov KBI have increased slightly. The main reasons for the first case are related to structural (loss of competitiveness) and cyclical problems. With regard to government research, it may have been affected by the changes in budgeting policy (austerity).

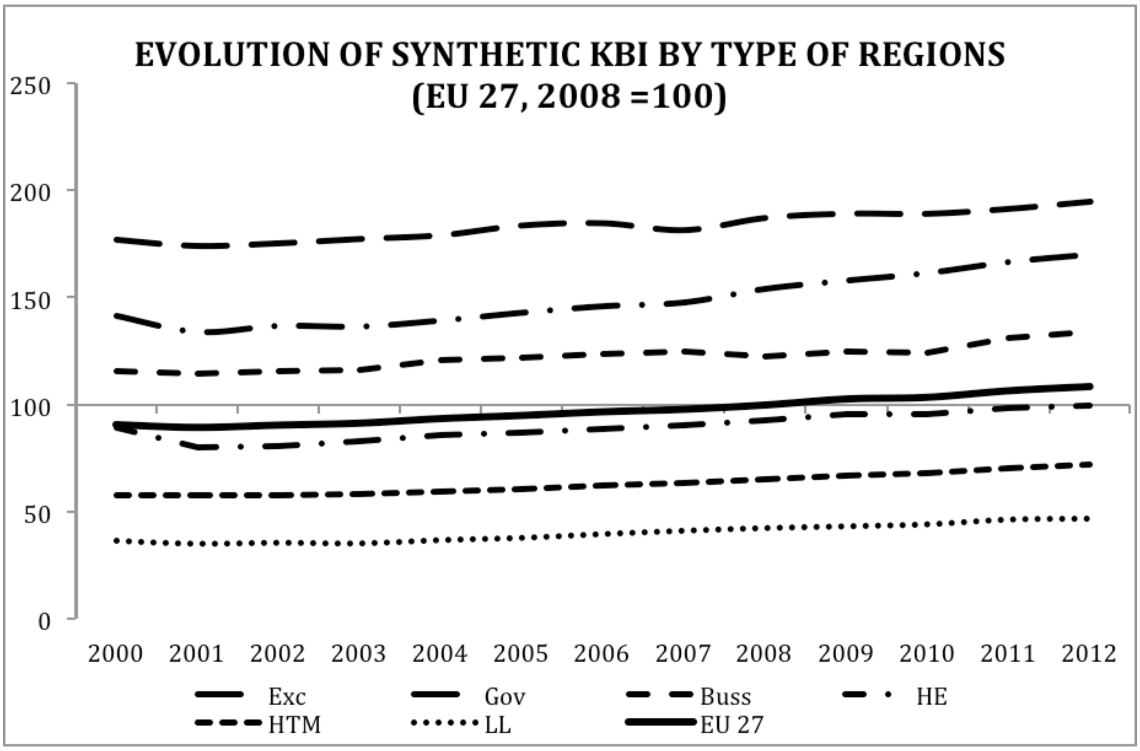
On the other hand, the high geographical concentration of knowledge has decreased along the period, and the variance among regions has therefore clearly reduced along the period. The standard deviation of synthetic KBI has continuously decreased since 2000, as seen in Figure 3. The same behavior has been observed in every component of KBI except for Gov KBI, and it has been particularly intense in HRST KBI, HE KBI and Buss KBI. Then, a spatial convergence of KBI may be observed in Figure 4, where the evolution of synthetic KBI for each type of region is registered. Overall, LL regions have increased their knowledge bases at higher rates, and regions with the highest levels of KBI have lost a small amount of their advantage. The process of regional convergence may have been a result of EU regional policy, but this analysis is out of the scope of this paper.

Overall, evolution in KBI has shown improvements in all types of regions in HRST KBI and Buss KBI and HE KBI (Figure 3). On the other hand, LL regions have increased in all of their indices above the EU mean, except in KIBS KBI, displaying some spatial reallocation along these years. Conversely, Excellence regions have shown a variation in KBI bellow the EU mean, except in HE KBI.

A joint-examination of the evolution of knowledge base Indices using CA applied to the variation rates in KBI has shown several different behaviors that have been compared to the previous analysis. On the one hand, one may observe very specific individual paces in a small number of regions not to be mentioned here. On the other hand, the most noteworthy results should be highlighted.

Firstly, a subgroup of 'Government' regions has experienced a relevant reallocation of research from government to business and HE, highlighting the chief role of several capital cities in Eastern European countries. Secondly, a large number of regions included in 'LL' and 'HE' and 'KIBS' groups have also boosted business research. Thirdly, government research has also increased in many regions of the 'LL' group. Finally, spatial differences in the rest of the indices have been of minor interest.

Figure 3. Evolution of synthetic KBI by type of regions (EU-27, 2008=100)



CONCLUSIONS

Knowledge has become a key assessment for competitiveness and success in the new age of economic performance at the beginning of the 21st century. This contribution to growth has become decisive to add value to production through the increase of productivity and the application of new ideas and technologies.

In this context, this study has explored knowledge base allocation in European regions through building annual series of a synthetic KBI and their partial components to register their main elements. This has been the main added value of this work.

Building these indices has been a difficult task, of which the main difficulties have arisen from the lack of data, which have had to be imputed. Synthetic KBI is a weighting index composed of 12 variables grouped into 6 representative components of the local accessibility of sources of useful knowledge in business to improve territorial innovation and competitiveness.

The availability of annual continuous series of synthetic KB Indices and their components can be useful to test the hypotheses and to monitor the evolution of policies. The main usefulness of these indices is to serve as indicators to appreciate the progress in improving the building of a knowledge-based economy. Then, among other aspects, it may serve to monitor the progress in the technological regional policy and the achievement of the priorities of the 2020 strategy.

Nevertheless, this study could also suffer from several weaknesses that should be improved in the future. The main weakness refers to the availability of data. Then, the synthetic KBI could be ameliorated if data were broader in terms of time (more years and variables) and space (other regions outside the EU).

With regard to existing data analysis, data standardization to the EU mean and prescriptions proposed with this benchmarking might be different if other goals were fixed, taking into account the policy priorities in this field.

With these cautions and caveats in mind, the applied analysis has shown different territorial patterns in knowledge base in the EU-27 regions. A great spatial disparity has been observed for variables related to the research effort in fields such as public research and business research essentially. However, regional differences in HRST KBI have been less important.

Overall, two morphologically large and different spaces can be appreciated. The first one is sufficiently homogeneous, the values reached in KBI have been very high, and the wealthiest areas of the EU-27 are located in it. The second space has shown an uneven allocation of KBI, shaping very accused center-peripheral patterns in which regions hosting national capitals have reached very high levels of KBI while the remaining regions have obtained lower values.

Thus, the availability of annual continuous series of synthetic KBI and their components may be useful to explore and advance the analysis of regional technological paces and the formation of the regional knowledge base and related fields. Then, it may be used to study in a deeper way the relationship between regional KB and regions innovative capacity, the understanding of which is not yet complete.

NOTES

1. Some authors consider a third category, the knowledge incorporated, which refers to knowledge that is enclosed in processes, products, culture, routines, devices or structures (Gamble and Blackwell, 2002).
2. These techniques can be found in any textbook of Multivariate Analysis Techniques, e.g., Hair (2006).
3. The correlation between both variables was higher in Business research than in Higher Education research.
4. See the Correlation Matrix.
5. The process of clustering was performed in two steps. In the first, eight groups were established by the application of a K-mean method because the increase in the sum of quadratic errors in the step from eight to nine groups was a minimum. Nevertheless, the number of elements for every group varied greatly, ranging from 1 to 136. Then, the group with one element (London) was allocated in the group most similar to it, and the other three groups with a low number of members were clustered in one because they shared more similarities between them than with the remainder. The group with more elements that had reached the lowest values in the index was divided into two additional classes.
6. Sometimes, the restricted delimitation of the area of some national capitals has favored these results (Athens, Bratislavsky, Bucaresti, Lisbon, Prague, etc.).

7. Given the extension of this paper, the corresponding Maps are not deployed here, but they can be provided sending an email to the authors.

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APPENDIX

Table A1. Correlation matrix

	Ebuss	Egov	EHE	Rbuss	Rgov	RHE	RHCore	RHEd	RHOc	HTM	HTKIS	MKIS
Ebuss	1	0,27505	0,37034	0,82239	0,13255	0,14685	0,35296	0,21373	0,24942	0,42369	0,44198	0,35257
Egov	0,27505	1	0,35077	0,30643	0,76073	0,22875	0,39241	0,1639	0,17632	0,09157	0,45286	0,31325
EHE	0,37034	0,35077	1	0,41432	0,17588	0,60887	0,4571	0,23222	0,11241	-0,0239	0,3813	0,34895
Rbuss	**0,82239**	0,30643	0,41432	1	0,27594	0,2639	0,47322	0,21694	0,28483	0,33825	0,54665	0,43081
Rgov	0,13255	**0,76073**	0,17588	0,27594	1	0,28007	0,42554	0,07585	0,23814	0,0222	0,49077	0,39166
RHE	0,14685	0,22875	**0,60887**	0,2639	0,28007	1	0,45241	0,47459	-0,1483	-0,1555	0,47287	0,36217
RHCore	0,35296	0,39241	0,4571	0,47322	0,42554	0,45241	1	0,58895	-0,0034	-0,0847	0,649	0,60239
RHEd	0,21373	0,1639	0,23222	0,21694	0,07585	0,47459	**0,58895**	1	-0,4354	-0,1434	0,38806	0,31171
RHOc	0,24942	0,17632	0,11241	0,28483	0,23814	-0,1483	-0,0034	-0,4354	1	0,42749	0,24773	0,37527
HTM	0,42369	0,09157	-0,0239	0,33825	0,0222	-0,1555	-0,0847	-0,1434	**0,42749**	1	0,03629	-0,0597
HTKIS	0,44198	0,45286	0,3813	0,54665	0,49077	0,47287	0,649	0,38806	0,24773	0,03629	1	0,7236
MKIS	0,35257	0,31325	0,34895	0,43081	0,39166	0,36217	0,60239	0,31171	0,37527	-0,0597	**0,7236**	1