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Similarities and Differences in Competitiveness Among European NUTS2 Regions: An Empirical Analysis Based on 2010–2013 Data

Massimo Aria[1] · Giuseppe Lucio Gaeta[2,3] · Ugo Marani[2]

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Abstract Regional competitiveness is a concept whose definition and applicability is highly debated among scholars. Nevertheless, over recent years it has become widespread among policy makers and practitioners, especially in the European Union. In line with this diffusion a number of alternative composite indicators of regional competitiveness have been released. Instead of building a composite index, this paper carries out empirical analyses whose aim is to analyze the European NUTS2 regions' performance for those indicators that, according to the literature, contribute to the definition of competitiveness. Results highlight the existence of a competitiveness divide between Northern European countries, which report better performances for most of the competitiveness indicators, and Southern/Eastern ones. The group of more competitive regions expands over time by including regions from Centre European countries while within peripheral regions a stable gap between regions where metropolitan areas are located and the others exists.

Keywords Regional Competitiveness · Cluster analysis · Structural equation modeling

Jel codes R11 · R19

✉ Giuseppe Lucio Gaeta
glgaeta@unior.it

Massimo Aria
massimo.aria@unina.it

Ugo Marani
marani@unior.it

[1] Department of Economics and Statistics, University of Naples Federico II, Naples, Italy

[2] Department of Human and Social Sciences, University of Naples L' Orientale, Naples, Italy

[3] cMet05 Inter-University Centre for Applied Economic Studies on Industrial Policy, Local Development and Internationalization, Naples, Italy

1 Introduction

Although territorial competitiveness is a highly controversial concept, over recent years enhancing national and regional competitiveness has progressively become a crucial policy target, and strategies to pursue it are at the top of decision makers' policy agendas (Bristow 2005; Kitson et al. 2004; Budd and Hirmis 2004; Camagni 2002).

More specifically, since regions are considered "key loci in the organization and governance of economic growth and wealth creation" (Kitson et al. 2004, p. 991), a notable concern for competitiveness is nowadays reported by regional policy makers and practitioners (Bristow 2010). In the EU this concern is crucial to the point that making regions more competitive might be considered the overarching purpose of the 2014–2020 cohesion policy.

While there is not any totally agreed definition for regional competitiveness, and in some perspectives it remains an elusive concept (Kitson et al. 2004), one of the most accredited definitions claims that it consists in the ability of regions to be attractive in the short- and long-term for firms and residents by promoting firms' productivity, generating high and rising incomes, and improving the livelihoods of residents.

In parallel with the widespread use of the notion of regional competitiveness in policy arenas and with the evolution of the academic debate around its definition and applicability, nongovernmental organizations (NGO), institutions and scholars have started to deal with the elaboration of empirical strategies aimed at measuring it. The composite indicators resulting from these attempts are built through the aggregation of measures of those features of regional economies that are supposed to positively impact competitiveness according to the perspectives provided by different theoretical approaches, for instance export-base theories, endogenous growth theory, neo-Schumpeterian theory, evolutionary theory and institutionalist theory (Martin 2005).

This paper aims to contribute to this empirical literature by inspecting regional competitiveness in Europe before and after the Great Recession of 2008–2009. To this end, we propose our own elaboration of the European NUTS2 (*Nomenclature des unites territoriales statistiques*) data used to build a recently released and highly distinguished composite competitiveness index, namely the Regional Competitiveness Index (RCI–Annoni & Dijkstra 2017; Annoni and Kozovska 2010).

There are two reasons why relying on the data provided by this index should be considered appropriate for a study focusing on competitiveness. Firstly, to the best of our knowledge, RCI is the most up-to-date regional competitiveness index available. Secondly, unlike other cross-sectional competitiveness indices, it provides data that cover 2 years, 2010 and 2013. This ought to be considered highly important since regional competitiveness performance is a dynamic process, and comparisons over time must be preferred to static ones (Martin 2005). A 2016 version of the RCI data (Annoni et al. 2017) also exists but, unfortunately, was released only a few days after the completion of this paper, and therefore is not considered in the following analyses.

While, following most of the existing contributions, the RCI empirical analysis primarily aims to build a single composite competitiveness indicator, this paper relies on a Hierarchical Cluster Analysis (HCA) in order to provide a disaggregate assessment of regions' similarities and differences in performances for each of those dimensions that are supposed to be important in defining regional competitiveness.

In our opinion, such a HCA approach enables a more thorough investigation of the competitiveness performances reported by the European NUTS2 regions and allows to

acquire further insights into the heterogeneity of competitiveness among them. Indeed, some regions may theoretically report good performances for some competitiveness pillars and bad performances for others, and this combination of good and bad performances may make them similar to other regions and dissimilar from others. Knowing such similarities and dissimilarities allows a better understanding of regions that one may compete with, and regions that are in a better or worse condition than one's own. Composite indicators such as the RCI synthesize the original variables into one single value, which allows researchers to easily rank regions according to their overall competitiveness performance; HCA, meanwhile, gives insights into the original variables by "disseminating the information on the composite indicator, without losing the information on the dimensions of the indicators" (Nardo et al. 2005, p. 10). In other words, thanks to HCA information is 'not lost' in one single figure, as is the case of composite indicators.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of the existing composite measures of regional competitiveness, and presents the RCI and data used for its construction in detail. Section 3 illustrates the statistical methodologies applied in order to analyze the data. Section 4 presents and discusses our results. Finally, Sect. 5 concludes.

2 Regional Competitiveness and its Composite Measures

The notion of competitiveness was originally applied to firms in order to indicate their ability to profitably sell products and/or services and win or retain positions in their market compared with rivals. In this micro-level perspective, such an ability represents an essential requisite for entrepreneurs' survival and success.

This original concept has been progressively extended by analogy to nations. This has provided a new perspective on competition among countries, one notably different from those which interpreted trade performances as the result of comparative advantage based on resources endowment (i.e. the Heckscher and Ohlin model). Indeed, according to the competitiveness approach, a country's success essentially depends on productivity, which leaves space for policy interventions aimed at improving it.

This extension of the micro-level definition of competitiveness has been severely criticized. Indeed, on the one hand, countries and firms are highly different because nations do not fail while firms do. On the other hand, competition among countries can be a non-zero sum game, something that is likely to be infrequent when rivalry among companies is considered (Krugman 1994, 1996).

Furthermore, the idea that national competitiveness basically corresponds to a given country's productivity has also provoked criticism, since policies merely aimed at promoting it may turn out to be detrimental to citizens' living standards. Taking these latter criticisms into consideration, some of the many existing definitions of national competitiveness now share the idea that it indicates a country's capacity to simultaneously achieve high productivity and high levels of wages and living standards (Martin 2005).

One additional application of the competitiveness concept has been carried out by looking at regions, which represent a sort of a meso-level located between the macro (national) and the micro (firm) (Cellini and Soci 2002). Even Paul Krugman, who is the most severe critical voice against the vagueness of the notion of national competitiveness, has conceded that the focus on regions turns out to be more appropriate than one based on nations. Indeed, while national economic performances are more driven by comparative advantage,

regional ones depend upon absolute advantage in producing goods or services, and this is driven by their capacity to attract production factors and therefore support productivity gains (Krugman 2005). In other words, "interregional growth rates [are]much more sensitive than international growth rates to differences in efficiency" (Krugman 2005, p. 37). Additionally, the migration of production factors at an interregional level should be considered easier than an international one, which, again, makes a competitiveness analysis more appropriate at region-level than at country-level.

Although the notion of regional competitiveness also raises conceptual issues (Borozan 2008; Martin 2005), a region's competitive advantage is commonly defined as its ability to offer an attractive environment for firms and residents in both the short- and long-term by providing those elements that promote productivity and wellbeing.

This definition focuses on issues relevant to firms but also to citizens and to their quality of life which has been suggested to be an essential feature of a competitive environment since it attracts talents and capitals (Rogerson 1999).

According to this definition of regional competitiveness, and the theoretical predictions concerning variables that should affect it, over recent years a number of alternative measures that aim to estimate regional competitiveness performances have been proposed.

Alongside proposals that focus on the competitiveness of regions inside one specific country (e.g. Huggins and Izushi 2008 for English regions; UNDP 2008 for Croatian regions; Huovari et al. 2001 for the Finnish case), international Europe-based comparisons are also available.

A first example is represented by the European Competitiveness Index (ECI), released in 2004 and 2006 by the Centre for International Competitiveness, involving Cardiff University and Aston Business School. Focusing on 116 NUTS1 regions from the EU25, Norway and Switzerland (Huggins and Davies 2006),[1] this index measures their competitiveness, defined as "the capability of an economy to maintain increasing standards of living for those who participate in it, by attracting and maintaining firms with stable or rising market shares in an activity" (Huggins and Davies 2006, p. 1). It was built by aggregating information provided by a number of indicators grouped into three categories—(a) creativity, (b) economic performance, (c) infrastructure and accessibility–which are considered to be essential elements of competitiveness.

In 2007 the Association of European Chambers of Commerce and Industry provided a different approach to analyzing regional competitiveness. Its Atlas of Regional Competitiveness (ARC–Eurochambers 2007) investigates competitiveness of 268 NUTS2 regions from 27 EU member states through a set of seven measures. In the opinion of the authors, each of the following measures represents a key factor for regional economic performance: employment and the labour market, training and lifelong learning, research and development/innovation, telecommunication networks, transport, and internationalization.

A third example is the Regional Competitiveness Index (RCI), a recently released and well respected composite measure of European NUTS2 competitiveness developed by the General Directorate (DG) for Regional Policy and the Joint Research Centre (JRC) of the European Union (EU).

The building of this index moves on from the definition of competitiveness recalled in Sect. 1, and is based on methodology originally suggested by the World Economic Forum (WEF) for the estimates at the country-level of the Global Competitiveness Index (GCI).

[1] The number of regions included in the study was lower in the first edition of the index.

According to this methodology, the building of the RCI is realized through three steps.

In the first step, by looking at the literature linked to export-base theories, endogenous growth theory, neo-Schumpeterian theory, evolutionary theory and institutionalist theory, the following three groups of competitiveness factors are identified: (1) basic factors of competitiveness, which are supposed to be particularly crucial for less developed regions(quality of institutions, macro-economic stability, infrastructure, health, quality of primary and secondary education); (2) Factors that observe the efficiency of regional economies as observed by looking at higher education and lifelong learning, labour market efficiency, and market size; essentially, these factors measure the degree to which a given economy has a higher potential skilled labor force and more structured labour market than another; (3) Factors that are considered to be particularly important for the most advanced economies, since they contribute to defining a region's capacity to promote innovation, such as technological readiness, business sophistication.

In the second step, for each of the eleven factors (pillars), a sub-index is built by drawing on a wide set of variables that are identified after a selection carried out among a number of candidate indicators by relying on multivariate statistical analyses aimed at assessing the internal consistency of each pillar. A synthetic index for each pillar is then calculated as the arithmetic mean of transformed (to make them more symmetric, linear, and constant in variance) and standardized original variables.

In the final step, one sub-index is calculated for each of the three groups of competitiveness factors presented so far. This is carried out by simply computing the arithmetic mean of the related pillar scores. These sub-indices are lastly aggregated into the final RCI by weighting their importance for each region consistently with the regional development stage. This development stage is assessed by looking at the regional GDP at current market prices measured as PPP per inhabitants and expressed as a percentage of the EU average—GDP%. This means that for regions in a lower stage of development, the group of basic competitiveness factors was considered more important than the ones concerning innovation.

3 An Empirical Analysis of the Competitiveness Performance of Regions

3.1 Data

As has already been highlighted in the introductory section of this paper, our empirical analysis relies on the NUTS2- level data that were used for the calculation of the RCI. Nevertheless, compared with the data used in building the RCI, those employed here are restricted for three reasons.

Firstly, the number of base variables considered by the RCI researchers in order to build the scores of the RCI pillars was slightly modified between the first and second editions of the index. As suggested by the RCI authors "comparing the RCI over time is complicated because each edition of the index incorporates improvements and slight modifications. These do not affect the overall structure of the index, but they limit the possibilities to measure change over time" (Annoni et al. 2017, p. 13). In order to ease comparability of data across the 2 years under investigation, we recomputed the pillars' scores for the 2 years by relying exclusively on the base indicators that were simultaneously included in the two RCI editions. In our opinion this strategy eases comparability of our results over time. Indeed, as long as we restrict our analysis to those base variables that are included in

both the 2010 and 2013 versions of the RCI index, any change in the scores of a region's pillars might be exclusively attributable to its performance. On the other hand, by allowing differences among sets of base variables used in 2010 and those used in 2013, any change in a region's performance might depend, at least in part, on these variables' changes. This would bias the comparison between the results achieved by regions at different time points.

Secondly, those pillars that were mostly calculated on a national basis (quality of institutions, macro-economic stability, quality of basic education) are not considered in our elaboration. This allows us to focus specifically on those competitiveness factors that distinguish regions even within the same country. The 2013 RCI version of the quality of institutions pillar included a regional sub-pillar that, nevertheless, was not included in the 2010 version of the index and, therefore, was discarded because of the reason stated above.

Thirdly, we had to discard one pillar whose base indicators were totally changed from the first edition of the RCI to the second one (business sophistication), as this change made any comparison impossible.

In sum, our analysis is based on the basic variables used for building the following seven RCI pillars: availability of infrastructure, health, higher education and lifelong learning, labour market efficiency, market size, technological readiness, and innovation. Only those variables that were considered for each pillar in both the two RCI editions were included in our dataset. All the others, meanwhile, were discarded. This was necessary in order to calculate comparable pillars' indices for the 2 years under investigation.

Table 1 provides an overview of the variables considered in our study. For each of the variables, the table shows the reference year considered by the 2010 and the 2013 edition of the RCI. It is worth noting that the years taken into account for measuring the competitiveness dimensions show some heterogeneity also within each RCI edition. This is probably due to data availability issues. As a matter of fact, for some of the dimensions the RCI2010 data actually observe the condition of European regions just before the start of the 2008–2009 Great Recession or at least at its first year, in 2008, while the RCI2013 data observe the same set of regions right after this period (most of the variables used for measuring the dimension are observed in 2010–2011).[2] This is the case of the following dimensions: infrastructure, higher education and lifelong learning, labour market efficiency. In this perspective, a comparison of data collected by the 2010 and 2013 editions of the RCI allows us to inspect the effects of the 2008–2009 recession on these European regions' competitiveness dimensions. For other competitiveness dimensions, instead, the identification of RCI2010 data as the pre-crisis measure and of RCI2013 data as the post-crisis measure is definitely less clear-cut. This circumstance also supports our approach of a disaggregate analysis of the RCI dimensions instead of building a single competitiveness index.

Our final dataset includes 262 NUTS2 European regions from 27 EU member states. NUTS2 changes/merges between the two periods considered have been checked by relying on the Eurostat history of NUTS webpage.[3] In order to take them into account, when needed regions were merged/merged by using population data as weights. Regions from

[2] According to Eurostat data, consecutive quarters of negative economic growth have been observed in EU28 from Q2 2008 until Q2 2009 and from Q4 2011 until Q2 2012. Nevertheless, the length and strength of recession periods significantly varies across countries.

[3] The webpage is available at the following address: ec.europa.eu/Eurostat/web/nuts/history [last Access on 15/9/2017].

Table 1 Base variables considered for building each of the competitiveness pillars under examination. For each of the variables the corresponding reference year considered by the 2010 and 2013 edition of the Regional Competitiveness Index (RCI–Annoni and Dijkstra 2010 and 2013) is reported

Pillar	Variables	Reference year in RCI2010 (Annoni and Dijkstra 2010)	Reference year in RCI2013 (Annoni and Dijkstra 2017)
Infrastructure	1. Daily number of flights accessible with 90′ drive	2007	2010
Health	1. Road fatalities	Average 2004–2006	Average 2008–2010
	2. Healthy life expectancy	2007	2010
	3. Infant mortality	2007	2010
	4. Cancer death rate	Average 2006–2008	Average 2007–2009
	5. Heart disease rate	Average 2006–2008	Average 2007–2009
	6. Suicide rate	Average 2006–2008	Average 2007–2009
Higher education and lifelong learning	1. Share of population 25–64 with higher education	2007	2011
	2. Lifelong learning	2007	2011
	3. Early school leavers	Average 2006–2007	Average 2009–2011
Labor market efficiency	1. Employment rate (excluding agriculture	2008	2011
	2. Long-term unemployment	2008	2011
	3. Unemployment	2008	2011
	4. Labor productivity	2007	2009
	5. Gender balance unemployment	2008	2011
	6. Gender balance employment	2008	2011
	7. Female unemployment	2008	2011
Market size	1. Potential GDP in PPS	2007	2009
	2. Potential population	2000	2006
Technological readiness	1. Share of households with access to broadband	2009	2011
	2. Share of individuals buying over internet	2009	2011
	3. Share of households access to internet	2009	2011

Table 1 (continued)

Pillar	Variables	Reference year in RCI2010 (Annoni and Dijkstra 2010)	Reference year in RCI2013 (Annoni and Dijkstra 2017)
Innovation	1. Total patent applications	Average 2005–2006	Average 2007–2009
	2. Core creative class employment	Average 2006–2007	Average 2010–2011
	3. Knowledge workers	2006	2011
	4. Total intramural R&D expenditure	2007	2009
	5. Human Resources in Science and Technology	2008	2011
	6. Employment in technology and knowledge-intensive sectors	2008	2011

countries that were included only in one edition of the RCI index (i.e. Croatia) are not considered by our analysis.

3.2 Methodology

As a preliminary step of the analysis, we followed the RCI researchers and aggregated the original variables presented in Sect. 3.1 into synthetic indices, one for each of the competitiveness dimensions (pillars) considered by our study. According to the RCI methodology, these indexes were calculated as the arithmetic mean of transformed (to make them more symmetric, linear, and constant in variance) and standardized original variables.

The Box Cox transformations were applied by considering:

$$\phi_\lambda(x) = \frac{x^\lambda - 1}{\lambda} \quad if\ \lambda\dot{A}$$

$$\phi_\lambda(x) = log(x) \quad if\ \lambda = 0$$

Following the 2010 RCI edition manual, λ *values were chosen* according to the positive ($\lambda = 2$) or negative ($\lambda = 0.05$)asymmetry of the distribution and all the variables were transformed.

The building of these synthetic indicators was preparatory for the core of our empirical study, which consists in investigating similarities and differences among the European NUTS2 regions in terms of their performances for the competitiveness pillars. This analysis was carried out by means of a Hierarchical Cluster Analysis (HCA) applied to the 2010data, then replicated with the 2013 data. Analysis of Variance (ANOVA) and Tukey's Post-hoc test were used to inspect differences among the clusters resulting from the HCA. A number of studies show that Tukey's test is the most powerful post hoc procedure when the hypothesis of homoscedasticity, as in our case, can be considered plausible (Klockars et al. 1995; Kromrey and La Rocca 1995; Keppel and Wickens 2004).

HCA is a widely used statistical technique that has been applied by other studies, i.e. in order to inspect differences among European regions in terms of socio-economic development(Del Campo et al. 2008), and has been specifically used to study the competitiveness of regions within European countries (Kronthaler 2003).

It is a multivariate technique that allows us to gather together statistical observations by minimizing their distance within groups (clusters) and, at the same time, maximizing distance among groups (clusters). HCA produces a hierarchy of clusters, from small clusters of very similar items to large clusters that include more dissimilar items. Hierarchical methods usually produce a graphical output known as a dendrogram, or tree, that shows this hierarchical clustering structure (Ward 1963). Most hierarchical techniques fall into a category called agglomerative clustering. In this category, clusters are consecutively formed from objects. Hierarchical agglomerative clustering begins by finding the most similar two groups, based on the distance matrix, and subsequently merging them into a single group. This procedure is repeated, step-by-step, until all the samples have been added to a single large cluster. The final partition is identified by a distance criterion (Fernández and Gómez 2008). Starting from the bottom part of the dendrogram, the researcher decides to stop the agglomeration process when successive clusters are too far apart to be merged. Distance is assessed through similarity/dissimilarity measures (Kaufman and Rousseeuw 2009).

We used the Ward linkage with the squared Euclidean distance because it returned a high cophenetic correlation coefficient. The cophenetic correlation coefficient is a measure of how

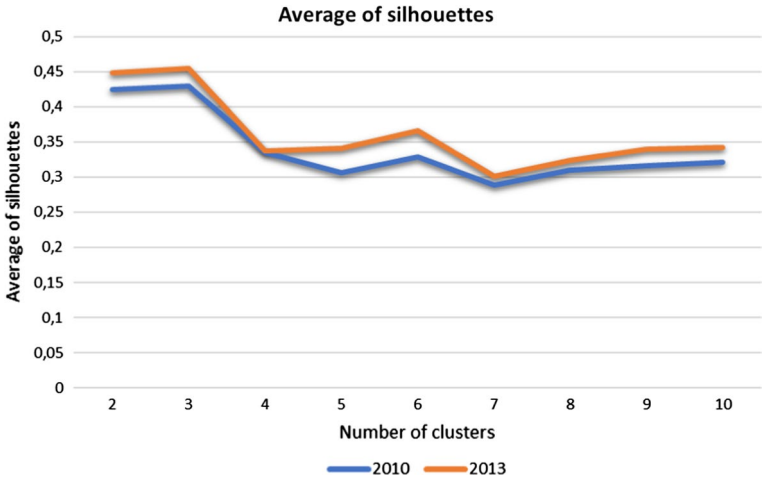

Fig. 1 Average of silhouettes for hierarchical clustering solutions with k = 2 to k = 10. Calculation based on 2010 and 2013 data. *Source*: our elaboration on 2010 and 2013 RCI data. (Color figure online)

faithfully a dendrogram preserves the pairwise distances between the original unmodeled data points (Sokal and Rohlf 1962).

The best partition among those available is selected by looking at the best possible compromise between quality (T_k) and complexity (K) (Hastie et al. 2009). We measure T_k as the average closeness of observations falling in the same cluster, where k is a given cluster of a partition formed by K clusters (with $k = 1, \ldots, K$). As consequence, we used the average silhouette criterion for assessing the natural number of clusters. The silhouette of an observation is a measure of how closely it is matched to data within its cluster and how loosely it is matched to data of the neighboring cluster (Rousseeuw 1987). A silhouette close to 1 implies the datum is in an appropriate cluster, while a silhouette close to -1 implies the datum is in the wrong cluster. The optimal number of clusters is one that maximizes the average silhouette over a range of possible values for K (Kaufman and Rousseeuw 2009).

While the preliminary step of our analysis follows part of the methodology suggested by the RCI researchers, the core of our investigation is different from it. Indeed, as has been shown in Sect. 2, the RCI methodology is based on the use of competitiveness pillars in order to build sub-indices which are then aggregated into a final index by using weights that vary according to the regions' development stages. In our analysis, meanwhile, we avoid the building of a composite competitiveness indicator, which allows us to focus on the competitiveness pillars. Therefore, we are able to identify those regions that present similarities and differences in terms of the competitiveness pillars observed in both 2010 and 2013. This provides a clear overview of a region's relative position in the European scenario.

4 Results: Similarities and Differences in Competitiveness-related Indicators Among European Regions (2010–2013)

HCA carried out on the 2010 data returned a three-clusters solution according to the average silhouette criterion (see Fig. 1). Figure 2 allows us to inspect the differences among these clusters by representing the mean and standard deviation values that they report for

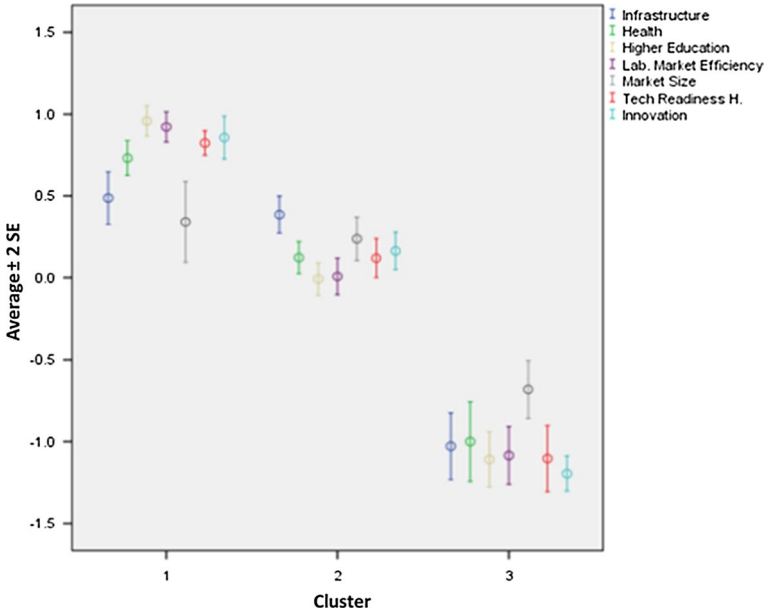

Fig. 2 Clusters' characterization in terms of the following pillars of competitiveness: availability of infrastructure, health, higher education, labour market efficiency, market size, technological readiness, innovation. Calculation based on 2010 data. *Source*: our elaboration on 2010 RCI data. (Color figure online)

Table 2 Pillars of competitiveness' mean and standard deviation by clusters, ANOVA analysis, Euclidean distance among clusters' centroids. Values calculated through the analysis focused on 2010

2010								
	Cluster 1 (n = 91)		Cluster 2 (n = 93)		Cluster 3 (n = 78)		ANOVA Test	
	Average	SD	Average	SD	Average	SD	F stat	P value
Infrastructure	0.487	0.765	0.386	0.546	− 1.028	0.904	106.764	< 0.001
Health	0.731	0.508	0.123	0.473	− 1	1.076	124.905	< 0.001
Highereducation	0.958	0.444	− 0.008	0.479	− 1.109	0.744	285.322	< 0.001
Lab. market efficiency	0.922	0.443	0.008	0.541	− 1.085	0.784	238.391	< 0.001
Market Size	0.341	1.178	0.238	0.637	− 0.682	0.779	32.302	< 0.001
Tech readiness	0.823	0.351	0.12	0.574	− 1.103	0.895	198.387	< 0.001
Innovation	0.857	0.623	0.164	0.55	− 1.196	0.476	291.892	< 0.001
Euclidean distance among clusters' centroids								
Cluster 1 versus Cluster 2	1.770							
Cluster 1 versus Cluster 3	4.750							
Cluster 2 versus Cluster 3	3.140							

each of the competitiveness pillars considered in the analysis. Tables 2 and 3 integrate this information by respectively providing a one-way ANOVA test that compares clusters' meanscalculated for the indicators of pillars used in the analysis and Tukey Post-hoc tests

Table 3 Tukey's Post Hoc Test for clusters' comparisons. Elaboration on 2010 data

2010			
	Cluster 1 versus cluster 2	Cluster1 versus cluster 3	Cluster 2 versus cluster 3
Infrastructure	0.101 (0.625)	1.515 (<0.001)	1.414 (<0.001)
Health	0.608 (<0.001)	1.732 (<0.001)	1.123 (<0.001)
HigherEducation	0.966 (<0.001)	2.067 (<0.001)	1.101 (<0.001)
Lab. Market Efficiency	0.914 (<0.001)	2.007 (<0.001)	1.093 (<0.001)
Market Size	0.103 (0.716)	1.023 (<0.001)	0.920 (<0.001)
Tech Readiness	0.703 (<0.001)	1.926 (<0.001)	1.223 (<0.001)
Innovation	0.692 (<0.001)	2.052 (<0.001)	1.360 (<0.001)

that specifically allow pairwise between clusters comparisons of performances for each of the competitiveness pillars (Jaccard et al. 1984). Bonferroni and LSD Post-hoc tests (Dunn 1961) were also run; they strongly confirm the results obtained by the Tukey tests and therefore were omitted in order to save space, but are available upon request.

According to our results, the first cluster is characterized by average performances decidedly higher than the second for most of the competitiveness pillars considered, namely: health, higher education, labour market efficiency, technological readiness, and innovation. On the other hand, it seems that there is not any clear distinction between cluster one and cluster two in terms of connection with the rest of the world (as measured by the infrastructure pillar) as well as in terms of market size. This result is not clear-cut when the composite RCI index is built. Lastly, the third cluster reports average values for all the competitiveness indicators that result as being significantly lower than those calculated for the first two groups of regions. It is worth noting that distances among the clusters' centroids, which are reported at the bottom of Table 2, suggest that cluster two is much closer to cluster one than to cluster three. Cluster three seems to be further away from the others, which suggests that it includes economically marginal regions that experience a notable competitiveness gap that concerns all the competitiveness dimensions taken into account by our study.

The map provided by Fig. 4 allows us to visualize the NUTS2 regions that belong to each of the clusters recognized. 91 regions, identified by the green color in Fig. 4, are included in the first cluster, the one that reports the highest values for most of the competitiveness pillars. All these regions are located in the centre-north of Europe. This includes NUTS2 regions from the Benelux area, and all of those from Denmark, southern Sweden and southern Finland. Alongside them, we also find most of the German regions, particularly those in the southwest, regions in southeast England and some of those in Scotland. Finally, the Île-de-France region also falls into this cluster.

As we already highlighted, NUTS2 regions that fall into cluster three (n = 78) are at the opposite side of the spectrum since they report values significantly lower than the other regions for all the competitiveness pillars considered by the HCA. Looking at Fig. 4, where this group of regions is represented in red, this cluster includes most of the geographically peripheral regions of Europe. This includes Southern European NUTS2 regions such as those of Greece, Spain and Portugal, southern Italy and the French Mediterranean island Corsica. Looking at Eastern Europe, most of the NUTS2 regions belonging to Latvia, Poland, Hungary, Romania, and Bulgaria also fall into this

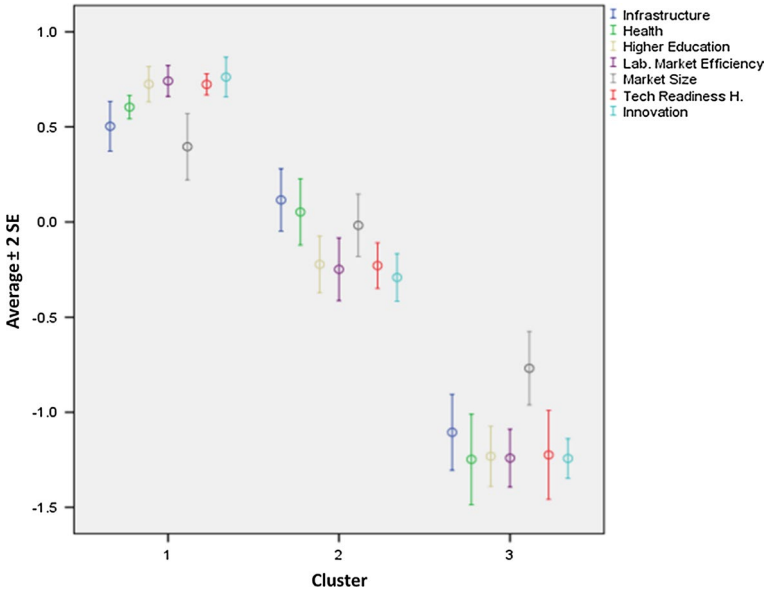

Fig. 3 Clusters' characterization in terms of the following pillars of competitiveness: availability of infrastructure, health, higher education, labour market efficiency, market size, technological readiness, innovation. Calculation based on 2013 data. *Source*: our elaboration on 2013 RCI data. (Color figure online)

cluster. A relevant exception is represented by those Eastern European regions where big metropolitan areas (e.g. capital cities) are located.

Cluster two includes 93 NUTS2 regions. According to our results, these are the regions that lie in an intermediate position (i.e. whose values for most of the pillars are lower than those reported by regions in cluster 1 and substantially higher than those reported by regions in cluster 3). In Fig. 4 this group of regions is identified by the beige color. This cluster includes Austria, most of France, part of northeast Germany, most of Sweden and Finland, northern Italy and northern Spain. This group is completed by those NUTS2 regions from Eastern European countries in which the country's capital city is located. The same applies to capital regions of Mediterranean countries like Spain, Italy and Greece.

On the whole, the analysis of the 2010 data provides four main pieces of evidence. Firstly, a North–South competitiveness divide between Northern/Central Europe and peripheral regions exists. Indeed, none of the regions in Southern European countries and almost none of those from Eastern Europe belong to the clusters characterized by high or intermediate scores for the competitiveness indicators scrutinized. Peripheral regions are undoubtedly distant from all the others in terms of competitiveness. Secondly, alongside the differences in performances for the competitiveness pillars between countries, which are reflected in the above-mentioned divide, significant differences also exist within countries. These are evident in countries such as Italy and Spain, but also concern England, Germany, Finland and Sweden. Thirdly, part of this variability in performance for the competitiveness pillars within countries is driven by larger metropolitan areas. Indeed, regions that include national capitals usually report better performances than the rest of the country. This trend is particularly visible for Eastern European countries, but also concerns Mediterranean countries.

Table 4 Pillars of competitiveness' mean and standard deviation by clusters, ANOVA analysis, Euclidean distance among clusters' centroids. Values calculated through the analysis focused on 2010

2013								
	Cluster 1 (n. = 133)		Cluster 2 (n = 62)		Cluster 3 (n. = 67)		ANOVA Test	
	Average	SD	Average	SD	Average	SD	F stat	P value
Infrastructure	0.503	0.755	0.116	0.645	− 1.105	0.817	104.153	< 0.001
Health	0.604	0.355	0.053	0.684	− 1.248	0.975	183.617	< 0.001
Higher education	0.725	0.536	− 0.223	0.586	− 1.232	0.646	261.555	< 0.001
Lab. market efficiency	0.741	0.471	− 0.249	0.651	− 1.241	0.625	288.441	< 0.001
Market size	0.395	1.007	− 0.018	0.647	− 0.768	0.791	389.381	< 0.001
Tech readiness	0.724	0.321	− 0.229	0.474	− 1.224	0.957	256.010	< 0.001
Innovation	0.762	0.604	− 0.292	0.493	− 1.243	0.427	321.346	< 0.001
Euclidean distance among clusters' centroids								
Cluster 1 versus Cluster 2	2.127							
Cluster 1 versus Cluster 3	4.790							
Cluster 2 versus Cluster 3	2.764							

Table 5 Tukey's Post Hoc Test for clusters' comparisons. Elaboration on 2013 data

2013			
	Cluster1 versus cluster 2	Cluster1 versus cluster 3	Cluster2 versus cluster 3
Infrastructure	0.387 (0.003)	1.608 (< 0.001)	1.221 (< 0.001)
Health	0.551 (< 0.001)	1.852 (< 0.001)	1.301 (< 0.001)
Higher education	0.948 (< 0.001)	1.956 (< 0.001)	1.009 (< 0.001)
Lab. market efficiency	0.990 (< 0.001)	1.982 (< 0.001)	0.992 (< 0.001)
Market size	0.413 (0.007)	1.163 (< 0.001)	0.751 (< 0.001)
Tech readiness	0.953 (< 0.001)	1.948 (< 0.001)	0.995 (< 0.001)
Innovation	1.054 (< 0.001)	2.005 (< 0.001)	0.951 (< 0.001)

Moving onto the examination of data collected in 2013, the picture depicted for 2010 shows slight changes. As before, one figure (Fig. 3) shows the mean and standard deviation of clusters for the competitiveness indicators considered in the analysis. This information is completed by the data reported by Tables 4 and 5 that illustrate the results of a one-way ANOVA test and Tukey Post-hoc tests (Bonferroni and LSD tests are omitted but available upon request) that compare the means of clusters calculated for the indicators used in the analysis.

When inspecting the 2013 data, the analysis also reveals the existence of three homogeneous groups of regions according to the average silhouette criterion (see Fig. 1). As in the 2010 analysis, the first group includes those regions that are in the most favourable condition. These are the regions that report the highest average values for all the pillars of competitiveness under investigation. The similarities between this cluster and cluster two in terms of connection with the rest of the world and market size, as reported in the analysis focused on 2010, do not appear to exist anymore in the 2013 analysis. At the opposite

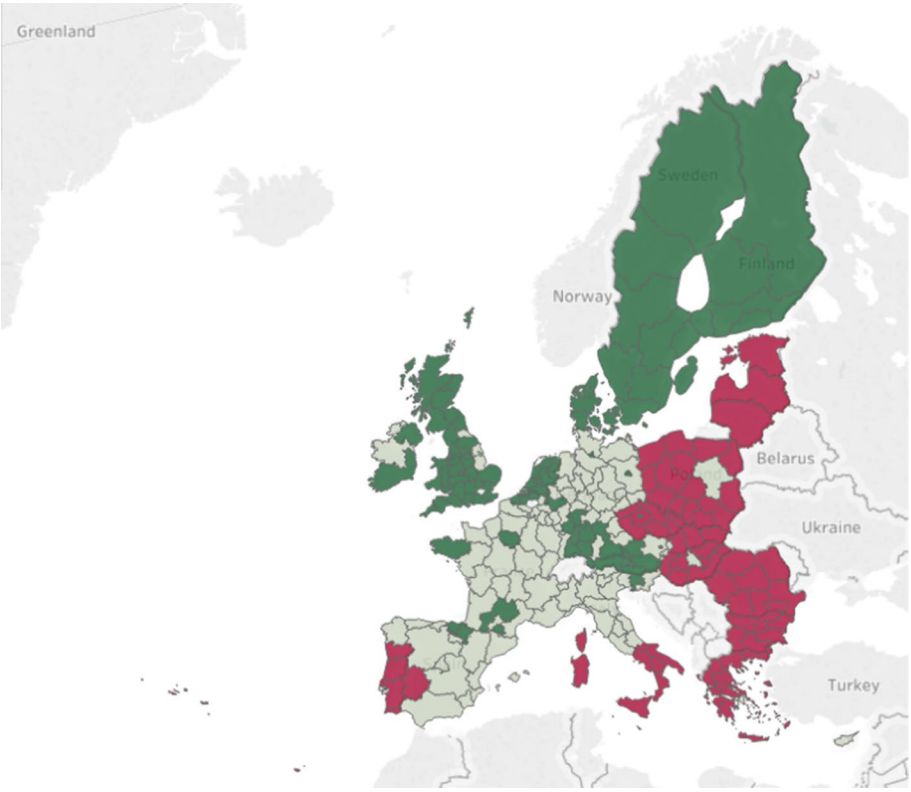

Fig. 4 European NUTS2 regions cluster membership as resulting from the hierarchical cluster analysis carried out on 2010 data concerning the following pillars of competitiveness: infrastructure, health, higher education and lifelong learning, labour market efficiency, market size, technological readiness, innovation. Legend: green = cluster 1, beige = cluster 2, red = cluster 3. (Color figure online)

side of the spectrum, cluster three reports the lowest average values in our sample for all the indicators inspected. Finally, an intermediate position is reported by cluster two.

Compared to the 2010 analysis, the investigation carried out on the 2013 data reveals that cluster one has a more variegated composition, since there is a significantly higher number of regions belong to it (n = 133). Nevertheless, the average values reported in 2013 by this cluster for most of the pillars under scrutiny are lower than those reported by the corresponding 2010 cluster. In other words, the group of competitiveness leaders has become bigger but less competitive over time. Comparing regions highlighted by the green color in Fig. 5 with those that show the same color in Fig. 4 allows us to identify regions that joined this cluster over time; these include regions from Austria England, Ireland, most of the German regions, the Madrid region in Spain, and some regions from France.

Consistently with the 2010 analysis, in 2013 one cluster (cluster three) includes those regions that report values lower than the others for all the competitiveness pillars examined. As in the 2010 analysis, this cluster includes regions from the peripheral areas of Europe, namely from the eastern border and from the Mediterranean area. Nevertheless, comparing this 2013 cluster with the corresponding 2010 cluster (red colour in Figs. 4 and 5), its size now appears to be smaller (only 67 regions instead of the 78 reported in 2010).

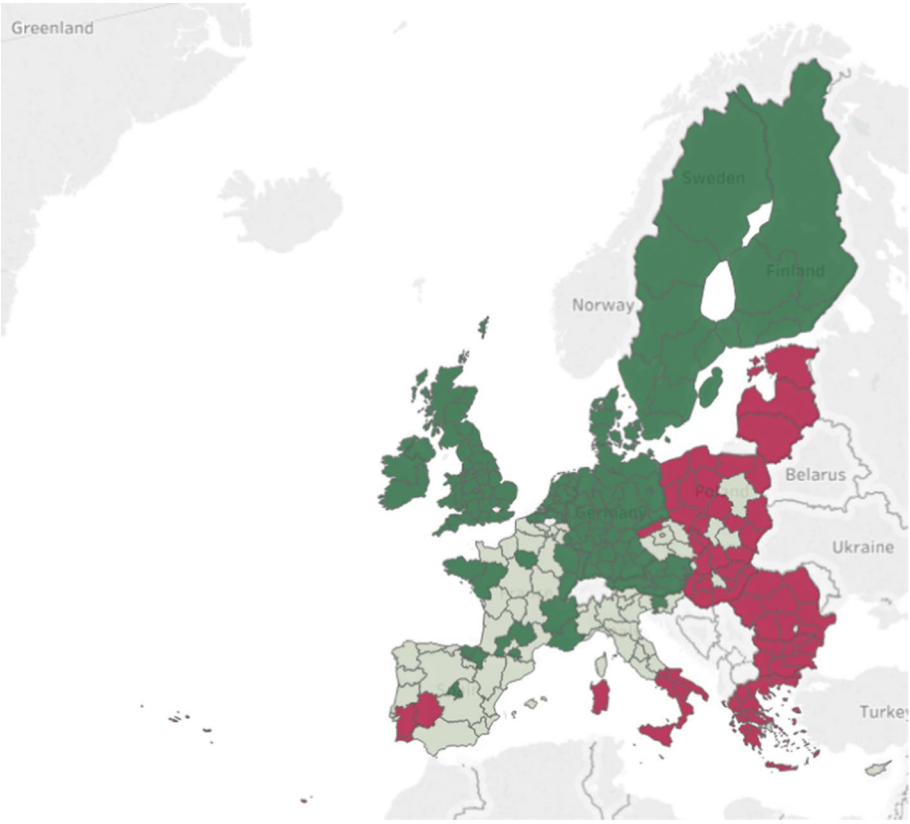

Fig. 5 European NUTS2 regions cluster membership as resulting from the hierarchical cluster analysis carried out on 2013 data concerning the following pillars of competitiveness: infrastructure, health, higher education and lifelong learning, labour market efficiency, market size, technological readiness, innovation. Legend: green = cluster 1, beige = cluster 2, red = cluster 3. (Color figure online)

Indeed, some Southern Spanish and Portuguese regions, which were in this cluster in 2010, are not included in it anymore, and the same applies to the French island of Corsica and to some regions in the Czech Republic. This suggests that these regions were able to improve their relative competitiveness position over time.

Finally, as in the 2010 analysis, cluster 2 includes all those regions that report intermediate values for the variables under inspection (beige colour in Figs. 4 and 5). Because of those regions that improved their competitiveness performance over time, as has been reported above, this group is sensibly smaller than the corresponding one identified through the 2010 analysis (62 regions instead of 93). Northern Italy, northern Spain, most of France and regions from East European countries where national capitals are located still belong to this cluster.

Distances among clusters, reported at the bottom of Table 4, suggest that NUTS2 regions that are in the most favorable position (cluster one) are even further away from the others than was reported in 2010, even if the increase in distance is not dramatic.

In sum, our analysis suggests that in 2010 and 2013 the European regions can be grouped into three clusters which are significantly heterogeneous among each other, but

Table 6 Regions'transitions among clusters during the 2010–2013 period

		2013			Totalnumber of regions
		Cluster 1	Cluster 2	Cluster 3	
2010	Cluster 1	90	1	0	91
	Cluster 2	43	50	0	93
	Cluster 3	0	11	67	78
Total number of regions		133	62	67	262

Number of regions moving from one cluster to another is reported

characterized by internal homogeneity. While the number of clusters is the same and their characterization is mostly unvaried between the 2 years considered, changes in the composition of these clusters are observed. The first cluster includes those regions whose performances are decidedly higher than the others for most of the competitiveness pillars (all of them in 2013). Regions from Northern European countries (Benelux, part of Sweden, Denmark,), from southeast England and from southern Germany belong to this cluster in 2010, but in 2013 it enlarges to embrace all of Germany, and most of England and part of France (movements between clusters are summarized in Table 6). The second cluster groups those regions whose performances are intermediate for all the competitiveness pillars. This group permanently includes regions from France, northern Spain, northern England and Ireland, as well from northern Italy. Some of its members in 2010, as has already been highlighted, join the first cluster of countries in 2013 (again, see Table 6). Cluster three is made up of those regions whose performances are below the average for most of the competitiveness pillars, except for market size and health. Regions from Southern Europe and Eastern European countries belong to it permanently during the period considered.

While the overall picture provided by our analysis is not dramatically different from the one provided by the RCI synthetic index, some differences arise in both the 2010 and the 2013 analyses.

Some regions show a high ranking in the 2010 RCI while our 2010 analysis only classifies them in the intermediate cluster, i.e. cluster 2. This is the case of Luxembourg, Madrid, Bratislava, Ain and of the German regions Münster, Unterfranken, Hannover, Oberpfalz, Arnsberg, Schwaben and Bremen. On the contrary, some regions are classified in the first most competitive cluster by our analysis while they are not very high in the 2010 ranking of the RCI (e.g. the Italian region Lombardy, the English regions Highlands and Islands, Northumberland and Tyne and Wear; the French regions Bretagne and Midi-Pyrénées, the Spanish regions Basque Community and Navarra, the Swedish regions North Middle Sweden and Middle Norrland). Finally, some regions are included in our cluster 2 (intermediate cluster) despite being in the lowest part of the 2010 RCI raking; this is the case of the Italian region Valle d'Aosta and of the Spanish regions Canary Islands and Balearic Islands.

A lower number of differences emerge when comparing the 2013 RCI ranking with our 2013 analysis. Nevertheless, also in this case some RCI highly ranked regions are included in the intermediate cluster by our analysis (e.g. Bratislava in Slovakia, Hainaut and Province de Liège in Belgium, Prague and Central Bohemia in Czech Republic). At the same time, although being in the lowest part of the 2013 RCI raking some regions are classified in the intermediate cluster by our HCA (e.g. Czech Moravskoslezsko and Northwest, Nyugat-Dunántúl in Hungary and Dolnośląskie in Poland).

Overall, compared with the RCI ranking of regions, the HCA carried out by our study provides useful insights into regional heterogeneity in competitiveness. Indeed, our analysis allows to: (i) detect three groups of regions, of which one is characterized by competitiveness remarkably lower than the others; the RCI, instead, ranks the regions but does not provide any identification of groups of regions based on a similarity criterion; (ii) identify the competitiveness pillars that make the difference in characterizing those regions that are in a more favourable position. In the 2010 analysis, for instance, only some of the competitiveness pillars (namely, health, higher education, labour market efficiency, technological readiness, and innovation) play a role in distinguishing the most competitive cluster from the intermediate one. Two pillars (infrastructure and market size), instead, do not allow any difference between these clusters. This result is not observable when looking at the aggregate RCI2010 data.

5 Conclusion

Although the concept of regional competitiveness is vague and its definition is still highly debated, in recent years it has undoubtedly recorded a remarkable success among policy practitioners (Bristow 2010) and has progressively become crucial in designing regional policy strategies. For this reason, issues in measuring regional competitiveness have gained attention, and scholars as well as international organizations have dealt with the construction of regional competitiveness indices that can be very useful in order to inform policy makers.

This paper has contributed to this empirical literature. Our analysis is based on the empirical effort carried out by the researchers who developed the European RCI index in building synthetic measures of pillars of regional competitiveness such as infrastructure, health, higher education and lifelong learning, labour market efficiency, market size, technological readiness, and innovation. Our specific contribution consists in the use of Hierarchical Cluster Analysis for the examination of similarities and differences among European regions in terms of performances for these pillars. The adoption of this approach might be useful for scholar in order to analyze most recently released competitiveness data such as the 2016 RCI data (Annoni et al. 2017).

The analysis provided by this paper allowed us to identify three groups of regions that show comparable patterns in terms of competitiveness. More specifically, it allowed us to recognize those regions that are remarkably more predominant in terms of competitiveness, and distinguish them from other regions that are in an intermediate and in a significantly less competitive position.

A competitiveness divide between predominant Northern European regions and less competitive Southern/Eastern ones is observed. This divide slightly increases over time with central European regions joining the club of high competitive regions. Most of the peripheral European regions from Eastern countries and Mediterranean countries meanwhile remain static in the group of less competitive areas. Within these peripheral countries, an intra-national divide between metropolitan capital regions and others also seems to exist and persist over the time period considered.

Future research might benefit from data that would allow scholars to inspect the evolution of European regional competitiveness over a longer time period; this would facilitate an investigation of its determinants as well as well as its consequences.

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