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Filippo Ferrarini[1], Silvia Muzzioli[2], Bernard De Baets[3]

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[1] University of Modena and Reggio Emilia, Marco Biagi Foundation
Email: filippo.ferrarini@unimore.it
[2] University of Modena and Reggio Emilia, Department of Economics Marco Biagi and CEFIN
Email: silvia.muzzioli@unimore.it
[3] Ghent University, Department of Data Analysis and Mathematical Modelling
Email: bernard.debaets@ugent.be

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# A TOPSIS analysis of regional competitiveness at European level

Filippo Ferrarini,[a] Silvia Muzzioli,[a*] Bernard De Baets[b]

[a] *Marco Biagi Department of Economics, University of Modena and Reggio Emilia, Via Jacopo Berengario 51, 41121, Modena, Italy*

[b] *KERMIT, Department of Data Analysis and Mathematical Modelling, Ghent University, Coupure links 653, Ghent B-9000, Belgium*

## Abstract

Regional competitiveness is a complex, dynamic, and multidimensional concept that requires comprehensive measurement. However, the literature does not provide a clear-cut answer to the question of how to measure regional competitiveness. As a result, we revisit the EU Regional Competitiveness Index 2019 (RCI) using the *Technique for Order Preference by Similarity to Ideal Solution* (TOPSIS), a *Multiple Criteria Decision Making* (MCDM) method. By considering TOPSIS based on three different distance measures, i.e. the Manhattan, Euclidean and Mahalanobis distance measures, we assess regional competitiveness through a comparative approach, taking the RCI as a reference. First, as the RCI coincides with the TOPSIS ranking based on the Manhattan distance measure, we are able to provide a bridge between the two approaches and properly position our results. Second, the TOPSIS ranking based on the Mahalanobis distance measure is the most dissimilar to the RCI, highlighting the fact that the RCI pillars are highly correlated and that regional competitiveness is driven by interrelated factors. Finally, by comparing the TOPSIS rankings obtained, we observe that some regions remain in the same cluster of competitiveness as defined by the RCI across rankings, especially overperforming and underperforming regions, while other regions do not, since they are sensitive to the distance measure used, particularly those with a middle-ranking level of competitiveness. This comparative approach offers a fresh perspective on regional competitiveness that could be useful for policy-makers addressing territorial disparities.

*Keywords*: competitiveness, RCI, TOPSIS, regional economy, ranking, Europe

* Corresponding author
E-mail addresses: filippo.ferrarini@unimore.it (Filippo Ferrarini); silvia.muzzioli@unimore.it, via Jacopo Berengario 51, 41121 Modena (MO), Italy (Silvia Muzzioli); bernard.debaets@ugent.be (Bernard De Baets)

## 1. Introduction

The measurement of regional competitiveness is becoming essential for policy-makers. Since the stage of development of regional territories in the European Union (EU) is remarkably heterogeneous (European Union, 2011), it is crucial to assess the competitiveness of regions to address territorial disparities. However, due to the multidimensional nature of this concept, the literature does not provide a clear-cut answer to the question of how to measure regional competitiveness, and several approaches have been taken by scholars. In particular, the construction of indices is the predominant approach adopted by researchers (Borsekova, Koróny, & Nijkamp, 2021a; Bristow, 2010a; Huggins, Izushi & Thompson, 2013). Some authors use regression analysis to proxy a certain output variable with different input variables (Lengyel & Rechnitzer, 2013; Möbius & Althammer, 2020; Porter & Stern, 1999; Ülengin, Ulegin, & Önsel, 2002), while others construct an index for each specific aspect under investigation (OECD, 2017). One of the most common approaches for the measurement of regional competitiveness relies on the construction of a composite index, which amounts to the combination of several single variables examining a specific facet of the regional economy (Annoni, Dijkstra & Gargano, 2016; Huggins, 2003). This method is useful for comparing the competitive performance of territorial entities (Greene, Tracey, & Cowling, 2007).

Although there are periodic studies measuring competitiveness at national level with a composite index, such as the Global Competitiveness Report (see Bristow (2010a) for a comprehensive review), only a few national studies are available at regional level (Bronisz, Heijman, & Miszczuk, 2008; Huggins, 2003; Huovari, Kangasharju, & Alanen, 2002). The EU Regional Competitive Index (RCI) is one of the best-known periodic studies of regional competitiveness at EU level. This index measures the territorial competitiveness of the 268 EU regions at NUTS 2 (Nomenclature of Units for Territorial Statistics) level considering eleven pillars including: institutions, macroeconomic stability, infrastructure, health, basic education, higher education, labour market efficiency, market size, technological readiness, business sophistication and innovation. The RCI is useful for comparing regions with a similar level of economic development in order to coordinate policies across member states and address heterogeneities among territories, by identifying and implementing 'best practices' (Annoni & Dijkstra, 2019). However, questions have been raised about estimating regional competitiveness with an index, since rankings suffer from significant criticalities (Bristow, 2010a; Fernandez, Navarro, Duarte, & Ibarra, 2013). In particular, Bristow (2010a) highlights the weaknesses arising from relying on a single measure of competitiveness derived from an index: saying for instance that one region is 1.6 points more competitive than another may not tell us much about the real level of competitiveness of those regions. As a result, the present study intends to revisit the EU Regional Competitiveness Index 2019 (RCI) following a comparative approach by means of a popular Multiple Criteria Decision-making Method (MCDM), called *Technique for Order Preference by Similarity to Ideal Solution* (TOPSIS) (Hwang & Yoon, 1981). The TOPSIS method has been successfully used in many different fields (Behzadian, Otaghsara, Yazdani & Ignatius, 2012); however, its application to the measurement of territorial competitiveness is still limited (Bilbao-Terol, Arenas-Parra, and Onopko-Onopko 2019; Wang & Wang, 2014). The TOPSIS method ranks alternatives on the basis of a ratio based on the distance from a positive ideal solution and the distance from a negative ideal solution. Evaluating the effect of various distance measures is not unusual when applying TOPSIS (Behzadian et al., 2012; Chang et al., 2010). In this study we apply three different distance measures, namely the Manhattan, Euclidean and Mahalanobis distance measures (Mahalanobis, 1936). The motivation is the following: the Manhattan distance measure has already been used in the computation of indices (Sánchez de la Vega, Buendía Azorín, Segura & Yago, 2019), whereas the Euclidean distance measure is the default in the TOPSIS method (Ishizaka & Nemery, 2013). Neither the Manhattan nor the Euclidean distance measures consider correlations among indicators. In addition, the RCI does not take correlations into account, causing factors to be overweighted when they are positively correlated. However, regional competitiveness is considered as a multidimensional and intertwined concept (Annoni & Dijkstra, 2019) and the literature highlights the fact that its dimensions are normally not independent (Aiginger & Firgo, 2017; Cheng, Long, Chen, & Li, 2018; Dima, Begu, Vasilescu, & Maassen, 2018; Fagerberg & Srholec, 2017; Franco, Murcielago, & Wilson, 2014; Pike, Rodríguez-Pose, and Tomaney 2016; Pontarollo & Serpieri, 2021; Schwab, 2012). As a result, we also consider the Mahalanobis distance measure, which modifies the Euclidean distance measure by incorporating correlations. The outcome is three (different) rankings according to regional competitiveness (for the sake of brevity, we will refer to these rankings as the Manhattan, Euclidean and Mahalanobis rankings) that are compared with the RCI, which is taken as a reference. The comparison considers two different aspects: the analysis of rankings and the analysis of competitiveness clusters.

By applying three different distance measures, it is intended to address two main gaps in the literature on regional competitiveness. First, we contribute to the measurement of regional competitiveness through a comparative approach that may help to provide insights that were not evident through the use of a single measure of competitiveness, which inevitably provides only a single take on such a complex matter, as outlined by Bristow (2010a). Second, on the basis of evidence on regional competitiveness (Aiginger & Firgo, 2017, Pike et al. 2016; Pontarollo & Serpieri, 2021; Schwab, 2012), we consider regional competitiveness as an intertwined concept by also taking into account correlations.

In the following sections, we present a literature review on regional competitiveness and TOPSIS applications, then briefly introduce the RCI as the basis of our approach. In Section 3, we explain the methodology adopted, while comprehensively summarizing the results of the comparative evaluation in Section 4. We conclude with some overall remarks and point out some limitations of the study in the final section.

## 2. Literature review

### 2.1 Regional competitiveness and its measurement

Defining territorial competitiveness is problematic, controversial, and far from being comprehensively understood (Kitson, Martin & Tyler, 2004). Nevertheless, the measurement of territorial competitiveness is becoming essential for the planning and assessment of policies. At the beginning of the millennium, Porter analysed the concept of competitiveness at regional level and highlighted the influence of micro-level dynamics on the competitive capabilities of firms. Since then, the assessment of competitiveness at regional level has attracted more and more interest, as competitiveness is influenced by regional authorities, and regions are the spatial units that show the most dynamism in exploiting knowledge and attracting investment (Annoni & Dijkstra, 2017; Carayannis, Goletsis, and Grigoroudis 2018).

The concept of regional competitiveness derives from the notions of *comparative advantage* and *competitive advantage* (Kitson, Martin & Tyler, 2004). *Comparative advantage* means that countries can benefit from trade through specialization based on production factors (land, capital, and labour). This is reflected in the development of policies harnessing interregional comparative advantages. The Smart Specialization Strategy (S3), for instance, relies on the concept of the 'entrepreneurial discovery process', in which a region invests and specialises in the most promising sectors and in those fields where it has a comparative advantage and fertile ground for emerging specialisations. As a result, regions should embark on a discovery process with the help of local entrepreneurs, who can pinpoint what a country or region does best in terms of science and technology (Foray, David & Hall, 2009). *Competitive advantage,* on the other hand, focuses on the specific characteristics of a territory that allow firms to create and sustain a competitive advantage (Önsel, Ülengin, Ulusoy, Aktas, Kabak & Topcu, 2008). This is in line with Porter's cluster theory, since the productivity with which companies compete in a location is strongly influenced by the quality of the business environment (Porter, 1998).

Meanwhile, when analysing regional competitiveness, scholars argue that the main determinants of regional competitiveness are innovation (Carayannis et al., 2018; Ciocanel &

Pavelescu, 2015) and socio-economic territorial characteristics (Huggins et al., 2013; Lengyel, 2004). Innovation is an important factor of competitiveness, since regions are dynamic entities that accumulate knowledge and competences based on different actors interacting within a specific context, which is a potential source of innovation and complementary capabilities, moving along learning trajectories (Huggins, Izushi, Prokop & Thompson, 2014; Boschma, 2004). In this vein, Capello & Nijkamp (2009) argue that regional growth is endogenous, since it is embedded in a local socio-economic system that evolves as a result of the capacity of local actors to generate and acquire knowledge over a process of development. Furthermore, due to adaptation and integration, existing technologies tend to disappear in countries that have reached the innovation stage of development, and incremental improvements are not sufficient to increase productivity (Porter & Schwab, 2008). Hence, innovation is forward-looking since it replaces existing processes and techniques with new ones (Malecki, 2007).

Regional competition is inevitable, and as a result when measuring regional competitiveness, it is important to consider social and environmental factors such as human capital, institutional capital, knowledge capital, infrastructure capital, local consensus, and identity (Boschma, 2004; European Union, 2017b; Kitson et al., 2004). These are the endogenous and fixed elements that constitute the local resources that support regional economy and productivity, which are combined with exogenous and mobile resources (capital, productivity and knowledge) (Cappellin, 2003). Moreover, cultural, institutional, and social aspects are important since they lay the foundations for regional competitiveness and determine the ability of regions to be resilient and to adapt to an unstable environment (Bristow, 2010b; Christopherson, Michie, & Tyler, 2010; Lengyel, 2004). Nevertheless, not all regions have the same resilience, giving rise to disparities in regional development. In Europe for instance, several authors highlight the fact that there are great differences and disparities in the stage of development of regions (Annoni & Dijkstra, 2019; Annoni, Dijkstra & Gargano, 2016; Pontarollo & Serpieri, 2020) since regions assign different importance to territorial capital for growth, resulting in different development patterns (Camagni & Capello, 2013). Möbius & Althammer (2020) for example, in their spatial econometric analysis of sustainable competitiveness of European regions, find that northern EU regions perform better in sustainable competitiveness than southern regions. Lengyel & Rechnitzer (2013), on the other hand, in their study of regional competitiveness of central European regions, find that post-socialist regions constitute a detached group that is more competitive than other central European regions. To this end, the measurement of regional competitiveness is becoming essential for policy-makers since a sustained increase of competitiveness is an indispensable prerequisite for growth (Sánchez de la Vega et al., 2019).

However, the measurement of competitiveness at regional level is not clearly defined (Kresl & Singh, 1999). Although there are numerous studies measuring competitiveness at national level, country indices fail to analyse subnational trends and performance gaps across regions (Huggins et al., 2013). Therefore, regional competitiveness is attracting increasing attention from scholars and policy-makers. In the literature different approaches are adopted to the measurement of territorial competitiveness, such as regression analysis (Lengyel & Rechnitzer, 2013; Möbius & Althammer, 2020; Porter & Stern, 1999; Ülengin et al., 2002) simple indices (OECD, 2017) or composite indices (Annoni & Dijkstra, 2019; Önsel, et al., 2008). Nevertheless, although the TOPSIS method has been proven to be an effective method to measure the competitiveness of territories (Wang & Wang, 2014), its application to the measurement of regional competitiveness is still limited.

Due to its simplicity and ease of use, the TOPSIS method has proven to be a successful method in different fields, such as business management, human resource management, engineering and logistics (Behzadian et al., 2012). The TOPSIS method involves finding the best alternative among a range of alternatives and ranking all alternatives in the presence of multiple criteria (Kuo, 2017). The procedure of TOPSIS consists of the following six steps: (1) normalize the decision matrix, (2) compute the weighted normalized decision matrix, (3) determine the positive ideal solution and the negative ideal solution, (4) calculate the distance of an alternative from the positive ideal solution and from the negative ideal solution, (5) calculate the relative proximity of an alternative to the positive ideal solution, (6) rank alternatives in descending order.

The literature offers a few reports on the application of the TOPSIS method for the measurement of regional competitiveness. Wang & Wang (2014) use the Mahalanobis distance measures for assessing the competitiveness level of Chinese high-tech provinces, whereas Zhang, Gu, Gu & Zhang (2011) use TOPSIS for the evaluation of the competitiveness of cities in China in tourism. To the best of our knowledge, there is only one application of the TOPSIS method to the RCI. Bilbao-Terol et al. (2019) extend the RCI 2013 with environmental indicators that provide information about the sustainable competitiveness of the regions. Using TOPSIS, they obtain an overall index of the attractiveness of NUTS 2 Spanish regions with respect to their sustainable competitiveness. The results show that environmental indicators should indeed be considered when measuring regional competitiveness. Moreover, they find that TOPSIS is a useful and straightforward method for measuring the competitiveness of regions. Nevertheless, they apply the TOPSIS method only to a limited number of territories; furthermore, they do not consider multiple distance measures, although this is a common practice when applying TOPSIS (Behzadian et al., 2012; Chang et al., 2010). In this study we extend the analysis of the RCI by using the TOPSIS method and applying three different distance measures to the 268 European regions at NUTS 2 level.

### 2.2 The Regional Competitiveness Index

Consisting of 11 pillars with more than 70 variables in three macro-dimensions, the RCI has been published by the European Commission every three years since 2010 and provides a comparable and multifaceted picture of the level of competitiveness of EU regions. It is the main periodic study of regional competitiveness in Europe, and it covers 268 territories at NUTS 2 regional level. The NUTS classification is a hierarchical system for dividing the territory of the EU into spatial units from NUT-1 (larger) to NUTS-3 (smaller) for statistical purposes (Bilbao-Terol et al. 2019). Since some regions contain different areas where people work and live, in some cases the RCI takes the functional urban area (FUA) as the territorial unit, and more rarely, two or more NUTS 2 regions are considered as a single territorial entity.

The pillars of the RCI cover different competitiveness aspects and are grouped into three macro-dimensions: the Basic dimension, the Efficiency dimension and the Innovation dimension. The Basic dimension consists of five pillars: Institutions, Macroeconomic Stability, Infrastructures, Health, and Basic Education, which represent the key enabling factors for regional competitiveness. The Efficiency dimension includes five pillars: Higher Education, Training and Lifelong Learning, Labour Market Efficiency, and Market Size, which represent the factors relating to the skilled labour force and labour market. The Innovation dimension consists of three pillars: Technological Readiness, Business Sophistication, and Innovation, which represent the factors characteristic of the most advanced economies. These three dimensions are conceptually nested, meaning that the Basic dimension is an enabling factor of the Efficiency dimension, which is instrumental for the Innovation dimension. In this way, regions that perform well on the Innovation dimension are expected to be good performers on the Basic and Efficiency dimensions (Annoni & Dijkstra, 2019). Therefore, we expect the pillars to be correlated. The assumption is that regions move along a development path that affects competences, and therefore their socio-economic needs and conditions are determinants of variations in competitiveness. As a result, regions make progress in their territorial priorities and innovation process (Annoni & Dijkstra, 2019; Boschma, 2004). The RCI is computed as a weighted average, the weights of which are related to the different stages of the development of regions, according to their GDP per head, following the Global Competitiveness Index (GCI) methodology (Schwab, 2018). Each pillar is calculated by computing the simple average of the indicators that compose it (see Annoni & Kozovska, 2010 for the full methodology). Likewise, the Basic, the Efficiency and Innovation macro-dimensions are computed by averaging across the pillars constituting each dimension. The structure of the RCI is depicted in Figure 1.

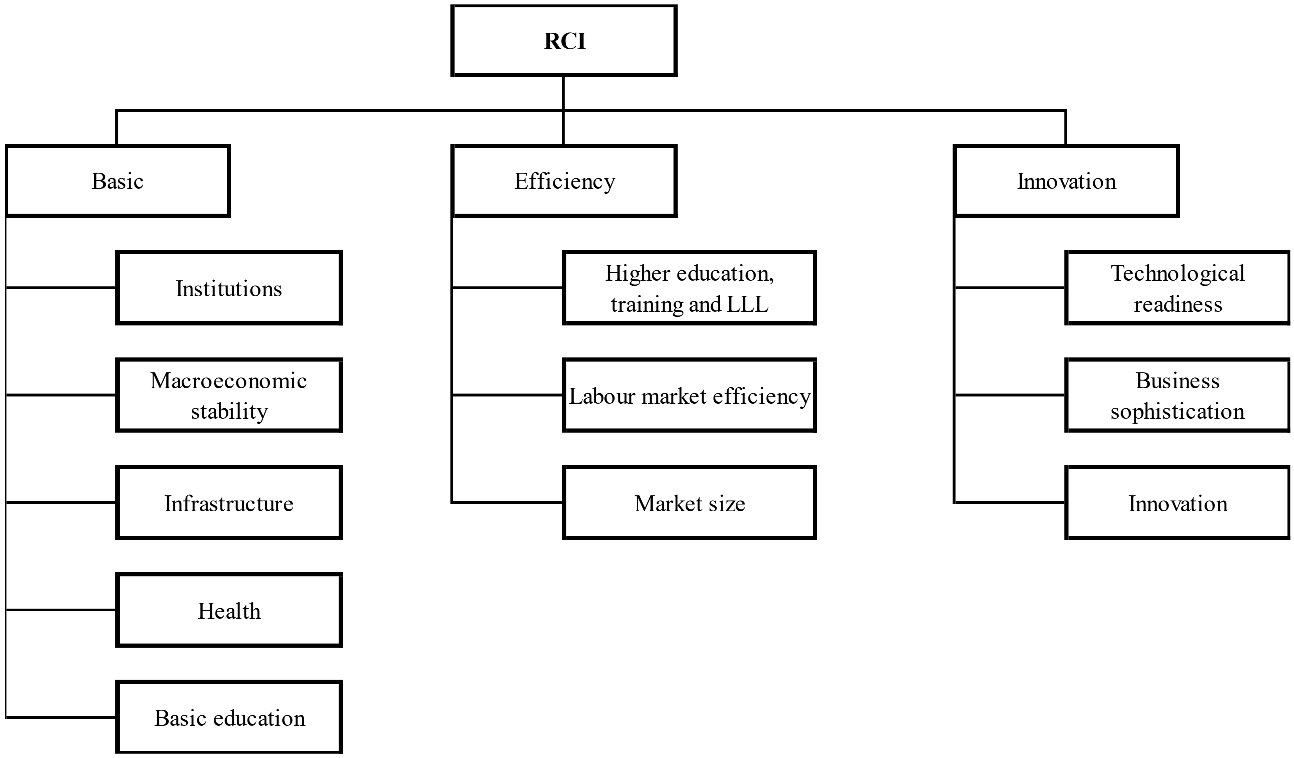



Figure 1: The RCI with the three dimensions and the eleven pillars

## 3. Data and methods

The first step was to download the data from the website of the European Union (European Union, 2019), already providing the standardized z-scores pillars of the RCI, which were then weighted according to the weighting scheme of the RCI (see Annoni & Dijkstra, 2019, 19), which depends on the regions' GDP level, forming a weighted normalized decision matrix $\boldsymbol{V} = \left(v_{ij}\right)_{m \times n}$.

The next step was to determine the positive ideal solution $A^+$ and negative ideal solution $A^-$ as $A^+ = (v_1^+, v_2^+, \dots, v_n^+)$ where $v_j^+ = \max\left(v_{ij}\right), i = 1, 2, \dots, m$ and $A^- = (v_1^-, v_2^-, \dots, v_n^-)$ where $v_j^- = \min\left(v_{ij}\right), i = 1, 2, \dots, m$. The positive ideal solution $A^+$is a hypothetical region that has the best score for each criterion and the negative ideal solution $A^-$ is a hypothetical region that has the worst score for each criterion.

The Manhattan, Euclidean and Mahalanobis distance measures were then used to calculate the distance $s_i^+$ from the positive ideal solution and the distance $s_i^-$ from the negative ideal solution for each region $a_i$. The superscript symbols $m, e$ and $p$ were used for the Manhattan, Euclidean and Mahalanobis distance measures, respectively.

For the Manhattan distance measure, we have:

$$s_i^{m+} = \Sigma_{j=1}^{n} \left| v_i^{+} - v_{ij} \right|, i = 1, 2, \ldots, m, \tag{1}$$

$$s_i^{m-} = \Sigma_{j=1}^{n} \left| v_i^{-} - v_{ij} \right|, i = 1, 2, \ldots, m. \tag{2}$$

The Manhattan distance considers indicators as independent and takes the sum of the absolute values of the differences. For the Euclidean distance measure, we have:

$$s_i^{e+} = \sqrt{\Sigma_{J=1}^{n} (v_i^{+} - v_{ij})^2}, i = 1, 2, \ldots, m, \tag{3}$$

$$s_i^{e-} = \sqrt{\Sigma_{J=1}^{n} (v_i^{-} - v_{ij})^2}, i = 1, 2, \ldots, m. \tag{4}$$

The Euclidean distance considers indicators as independent and takes the square root of the sum of the squared differences. Finally, for the Mahalanobis distance measure, we have:

$$s_i^{p+} = \sqrt{(v_i^{+} - v_{ij})^{T} \Sigma^{-1} (v_i^{+} - v_{ij})}, i = 1, 2, \ldots, m, \tag{5}$$

$$s_i^{p-} = \sqrt{(v_i^{-} - v_{ij})^{T} \Sigma^{-1} (v_i^{-} - v_{ij})}, i = 1, 2, \ldots, m. \tag{6}$$

The Mahalanobis distance measure takes the square root of the sum of the squared differences and considers correlations among indicators. In fact, it weights the squared differences by the inverse of the covariance matrix $(\Sigma^{-1})$. If the indicators are not correlated, the Mahalanobis distance measure coincides with the Euclidean distance measure.

Table 1 shows that the RCI pillars are positively and significantly correlated. The pillar Institutions is highly correlated not only with pillars of the Basic dimension, but also with pillars of the Efficiency and Innovation dimension, confirming that the quality of institutions is a key determinant for competitiveness (Aiginger & Firgo, 2017; Önsel, et al., 2008). Another relevant pillar is Innovation, which shows a high correlation with pillars of the Efficiency and Innovation dimensions. This is in line with the literature, which affirms that innovation is an important factor for competitiveness (Greene et al., 2007). One criticism is that correlation between indicators eliminates the effect of the different dimensions of the index (Wang & Wang, 2014). However, in the literature it is argued that indicators are normally not independent, and they tend to reinforce each other (Schwab, 2012). Hence, as argued by Huovari et al. (2002), the high correlation between indicators provides evidence that regional competitiveness is subject to cumulative causations, hence improvement in one dimension of competitiveness tends to improve other dimensions as well. Thus, considering correlations using the Mahalanobis distance measure is an important aspect of this study.

| | Basic | | | | | Efficiency | | | Innovation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
| 1. Institutions | 1.000 | | | | | | | | | | |
| 2. Macroeconomic Stability | .575** | 1.000 | | | | | | | | | |
| 3. Infrastructure | .550** | .292** | 1.000 | | | | | | | | |
| 4. Health | .438** | -.039 | .474** | 1.000 | | | | | | | |
| 5. Basic Education | .716** | .716** | .442** | .308** | 1.000 | | | | | | |
| 6. Higher Education and LLL | .642** | .473** | .327** | .271** | .457** | 1.000 | | | | | |
| 7. Labor Market Efficiency | .770** | .683** | .521** | .291** | .567** | .652** | 1.000 | | | | |
| 8. Market Size | .473** | .366** | .809** | .373** | .348** | .310** | .636** | 1.000 | | | |
| 9. Techonological Readiness | .929** | .552** | .646** | .484** | .646** | .588** | .775** | .603** | 1.000 | | |
| 10. Business Sophistication | .606** | .235** | .727** | .460** | .392** | .458** | .552** | .729** | .660** | 1.000 | |
| 11. Innovation Pillar | .676** | .401** | .686** | .501** | .459** | .731** | .734** | .690** | .724** | .757** | 1.000 |

**. Correlation is significant at the 0.01 level (2-tailed).

Table 1: The correlation matrix of the 11 pillars of the RCI

For each region $a_i$, we compute the relative closeness coefficient $C_i^*$:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}. \tag{7}$$

This relative closeness coefficient belongs to the unit interval [0,1] and constitutes the final score of the region. Regions are ranked in descending order of these scores, with the most competitive regions ranked in the highest positions, and the least competitive in the lowest positions. This final ranking is computed for each distance measure; thus, we obtain three (different) rankings, according to the three distance measures used.

To compare the rankings obtained, we use two permutation metrics: the Kendall tau and the Spearman footrule. The Kendall tau distance measure computes the dissimilarity $K(\sigma^r, \sigma^p)$ between two rankings $\sigma^r = (\sigma_1^r, \dots, \sigma_n^r)$ and $\sigma^p = \left(\sigma_1^p, \dots, \sigma_n^p\right)$ of the same set of objects (in our case regions) by counting the number of pairwise disagreements between these two rankings (Fagin, Kumar, Mahdian, Sivakumar & Vee, 2006). To facilitate the interpretation, we use the normalized Kendall tau $K^*$ (Beg & Ahmad, 2003):

$$K^*(\sigma^r, \sigma^p) = \frac{K(\sigma^r, \sigma^p)}{0.5n(n-1)}. \tag{8}$$

This value belongs to the unit interval [0,1]; if $\sigma^r$ and $\sigma^p$ are in the same order, then the value is 0, whereas if $\sigma^r$ and $\sigma^p$ are in the opposite order, then the value is 1. An alternative method to compute a distance between two rankings is the Spearman footrule (Diaconis & Graham, 1977), that computes the sum $F\ (\sigma^r, \sigma^p)$ of the absolute differences between the positions of all regions in the rankings. Also in this case, we use the normalized variant (Beg & Ahmad, 2003):

$$F^{*}(\sigma^{r},\sigma^{p}) = \frac{F\,(\sigma^{r},\sigma^{p})}{0.5n^{2}}\,. \qquad (9)$$

This value also belongs to the unit interval [0,1]; if $\sigma^r$ and $\sigma^p$ are in the same order, then the value is 0, whereas if $\sigma^r$ and $\sigma^p$ are in the opposite order, then the value is 1. In addition, we employ a candlestick chart for visualizing the position of the regions across rankings.

In the RCI, regions are grouped into eight clusters, according to their final score. Regions that score above 1 are considered the most competitive, while regions scoring below -1 are considered the least competitive. Between 1 and -1 there are six other clusters of regions, according to the scores obtained, (see Annoni & Dijkstra, 2019, 6). Since we are also interested in examining how the clusters of the RCI change their composition when the TOPSIS method is applied, we keep the cardinality of the clusters of the RCI for the clusters of the TOPSIS analysis in order to facilitate the comparison. For this last part, maps at NUTS-2 level are provided. They are elaborated using https://mapchart.net/ a website for map customization.

## 4. Results

### 4.1 The RCI and the rankings obtained by TOPSIS

In this section we show the results of the comparison of the Manhattan, Euclidean and Mahalanobis rankings with the RCI.

| Normalized Kendall tau | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1. RCI | 0 | | | |
| 2. Manhattan | 0 | 0 | | |
| 3. Euclidean | 0.046 | 0.046 | 0 | |
| 4. Mahalanobis | 0.143 | 0.143 | 0.107 | 0 |

Table 2: Normalized Kendall tau matrix

| Normalized Spearman footrule | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1. RCI | 0 | | | |
| 2. Manhattan | 0 | 0 | | |
| 3. Euclidean | 0.066 | 0.066 | 0 | |
| 4. Mahalanobis | 0.207 | 0.207 | 0.155 | 0 |

Table 3: Normalized Spearman's footrule matrix

Tables 2 and 3 present the matrices of the normalized Kendall tau $K^*$ (Eq. (8)) and the normalized Spearman footrule $F^*$ (Eq. (9)). Both tables show that the Manhattan ranking perfectly replicates the RCI since all regions are in the same order. This is an interesting finding, allowing us to take the RCI as the reference for our analysis. Sánchez de la Vega et al., (2019, 113) in constructing a regional competitiveness index of Spanish regions by means of the P-distance argue that "the Manhattan distance measure is used in the RCI, drawn up by the European Commission". Moreover, Euzenat & Shvaiko (2007, 124) note that "the weighted sum can be thought of as a generalisation of the Manhattan distance measure in which each dimension is weighted. It also corresponds to weighted average with normalised weights”. Therefore, given the fact that the computation of the RCI relies on a weighted average, this result suggests that the use of standardized data of the RCI results in the same ranking obtained by TOPSIS when the Manhattan distance measure is used. Moreover, we are able to provide a bridge between the two approaches, providing a starting point for considering other distance measures. The Euclidean ranking is similar to the RCI since $K^* = 0.046$ and $F^* = 0.066$. In fact, both the RCI and the Euclidean ranking fail to consider correlations between pillars. As expected, the Mahalanobis ranking is the one that presents the greatest dissimilarity from the RCI, having $K^* = 0.143$. and $F^* = 0.207$. This is not surprising since the Mahalanobis distance measure considers correlations among the pillars of the RCI, which are significant in our sample as shown in Table 1. Therefore, this finding supports evidence provided by other authors who showed that indicators driving regional competitiveness are interrelated (Aiginger & Firgo, 2017; Fagerberg & Srholec, 2017; Wang & Wang, 2014).

The candlestick chart in Figure 2 provides an overview of the position of regions across rankings. The x-axis represents the rank of each region in the RCI, while the y-axis refers to the rank of the same regions across the different rankings, specifically representing the RCI (orange dots), the Manhattan ranking (green dots), the Euclidean ranking (blue dots) and the Mahalanobis ranking (red dots). From the figure we can make two observations. First, the RCI coincides with the Manhattan ranking (the former not being visible in the figure), confirming the appropriateness of the TOPSIS method in measuring regional competitiveness. Second, in the Euclidean and Mahalanobis rankings, regions are ranked differently depending on the distance measure used. In some cases, the effect is the same since in both the Euclidean and Mahalanobis rankings, regions improve (or worsen) their position with respect to their position in the RCI, while in other cases the effect is opposite because sometimes in the Euclidean ranking regions improve their position, while they worsen their position in the Mahalanobis ranking and vice versa. The analysis shows that changes in the ranking are moderate in the Euclidean ranking since regions change nine positions on average, while they are remarkable in the Mahalanobis ranking since regions change 28 positions on average. Moreover, from Figure 2 it is evident that generally, regions that are ranked very high and very low in the RCI are subject to less variation in their position in the TOPSIS rankings, compared to the middle-ranking regions. For instance, Inner London is ranked second in both the RCI and the Manhattan ranking; moreover, it maintains the same position in the Euclidean ranking, whereas it is ranked first in the Manhattan ranking. The same holds for Guyane, which is ranked number 266 in the RCI and in the Manhattan ranking, while it improves just one position in the Euclidean ranking and two positions in the Manhattan ranking. The situation is different for middle-ranking regions such as Pays de la Loire for example, which is ranked in position 114 in both the RCI and Manhattan rankings, while it goes to position 102 in the Euclidean ranking and to position 30 in the Mahalanobis ranking. This finding might be attributed to the fact that, in line with Annoni & Dijkstra (2019), the dimensions of the RCI are conceptually nested, hence a good performer in the Innovation dimension is expected to be a good performer in the Basic and Efficiency dimensions, while bad performers in the Basic dimension are not expected to perform well on the Efficiency and Innovation dimensions. Therefore, as outlined by Bartkowska & Riedl (2012), this suggests a degree of stability for top-performing and bottom-performing regions, which may depend on their endogenous structural characteristics and socio-economic situation. At the same time, although middle-ranking regions perform well in some pillars, they present weaknesses in others, resulting in a greater sensitivity to the different distance measures. The current result underlines the fact that measuring regional competitiveness is difficult (Fagerberg & Srholec, 2017; Kresl & Singh, 1999), since depending on the method adopted, the position of a region in the ranking may be different. The positions of all 268 regions across the different rankings are provided in the annex.

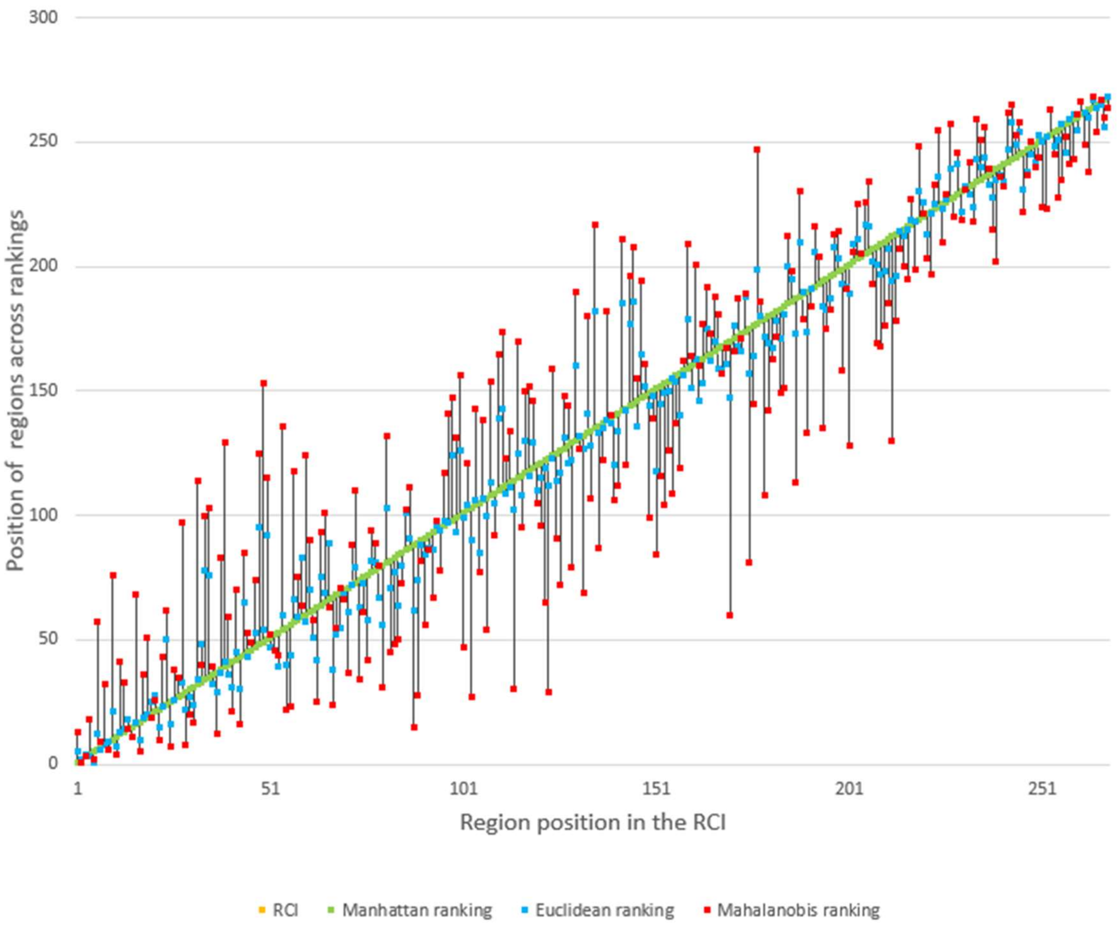



Figure 2: Positions of regions across rankings.

### 4.2 Analysis by clusters

As noted above, in the RCI, regions are clustered according to their stage of competitiveness depending on the final score of the index. Regions that score above 1 are considered the most competitive, while regions that score below -1 are considered the least competitive. In this part of the analysis, we examine how the composition of the clusters of the RCI changes when the TOPSIS method is applied. To do so, in the TOPSIS rankings clusters are subjectively predetermined by keeping the same cardinality as the clusters of the RCI to compare the results. Regions that switch cluster membership also change their competitiveness level with respect to the ranking considered. To facilitate the identification of the clusters, the RCI clusters are labelled according to their stage of competitiveness.

Table 4 shows the clusters of the RCI, which are ordered from cluster 1 (most competitive regions) to cluster 8 (least competitive regions). In addition, the number of regions in each cluster and the highest and lowest positions in each cluster are displayed according to the RCI. Examining the table, we observe that the composition of the RCI clusters is unaltered in the Manhattan ranking since it replicates the index, hence clusters are not subject to any variation. However, in both the Euclidean and Mahalanobis rankings, the composition of the clusters is altered. For instance, if we take cluster 1 (most competitive regions), it is evident that in the Euclidean ranking the composition of this cluster changes by 16.67% since one region is replaced by a new one. At the same time, the composition of the same cluster is altered by 50.00% in the Mahalanobis ranking, since three regions are replaced by three new ones.

The modification of RCI clusters differs depending on both the distance measure and on the typology of the cluster. For example, in the Euclidean ranking, cluster 6 (not very competitive regions) is the cluster that changes the most, while in the Mahalanobis ranking this is the case for cluster 4 (slightly competitive regions). Above all, we observe that the composition of the clusters varies the most in the Mahalanobis ranking, once again showing that the indicators of regional competitiveness are not independent (Fagerberg & Srholec, 2017; Huovari et al., 2002), the concept of regional competitiveness being multidimensional and intertwined (Annoni & Dijkstra, 2019). Moreover, it may be seen that in both the Euclidean and the Mahalanobis rankings, the clusters that are subject to most variation in their composition are the central ones (fairly competitive, slightly competitive, competitive, not very competitive regions), while extreme clusters (most competitive, highly competitive, hardly competitive, not competitive at all regions) are subject to less variation. This finding highlights the fact that the central clusters are more difficult to ascertain than the extreme ones, in line with the findings in Section 4.1.

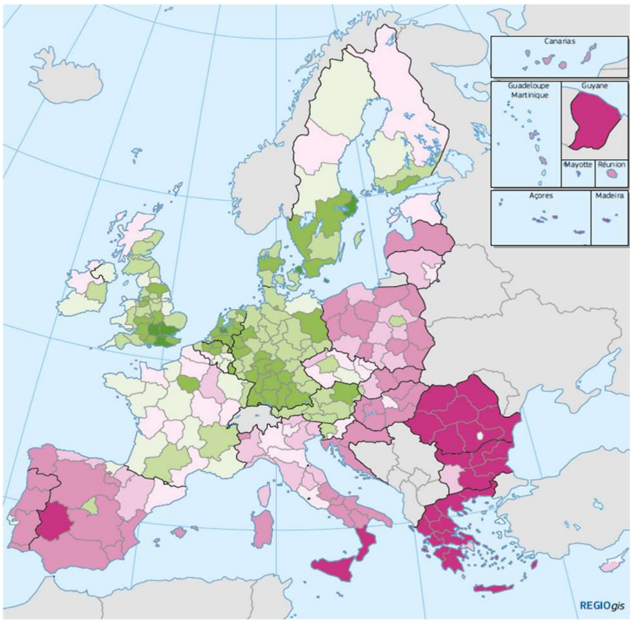
| Cluster | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| RCI score | > 1 | 0.5 – 1 | 0.2 – 0.5 | 0 – 0.2 | -0.2 – 0 | -0.5 – -0.2 | -1 – -0.5 | < -1 |
| Label | Most competitive | Highly competitive | Fairly Competitive | Slightly competitive | Competitive | Not very competitive | Hardly competitive | Not competitive at all |
| **RCI** | | | | | | | | |
| Ranks | 1-6 | 7-48 | 49-110 | 111-136 | 137-164 | 165-191 | 192-235 | 236-268 |
| N. of regions | 6 | 42 | 62 | 26 | 28 | 27 | 44 | 33 |
| **Regions that change cluster membership** | | | | | | | | |
| **Manhattan** | | | | | | | | |
| N. of regions | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| % | % | % | % | % | % | % | % | % |
| **Euclidean** | | | | | | | | |
| N. of regions | 1 | 8 | 11 | 8 | 11 | 11 | 9 | 5 |
| % | 16.67% | 19.05% | 17.74% | 30.77% | 39.29% | 40.74% | 20.45% | 15.15% |
| **Mahalanobis** | | | | | | | | |
| N. of regions | 3 | 20 | 33 | 23 | 20 | 15 | 19 | 8 |
| % | 50.00% | 47.62% | 53.23% | 88.46% | 71.43% | 55.56% | 43.18% | 24.24% |

Table 4: Clusters of regions according to the RCI and number of regions that change cluster when using the TOPSIS method

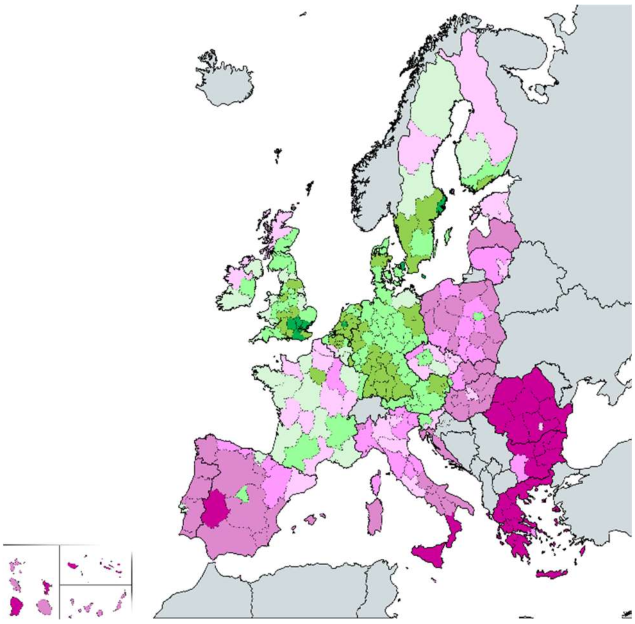
Figure 3 displays the maps of Europe according to the three TOPSIS rankings that are compared with the map of the RCI. It may be seen that the map of the Manhattan ranking is the same as the map of the RCI.

The map of the Euclidean ranking instead presents some differences. In fact, while some regions improve their competitive performance, such as some regions of northern Italy, and some in northern-eastern Greece or western Romania, as well as some regions of Bulgaria and Hungary, and some regions of central England, other regions worsen their competitive position, moving to a lower competitive cluster, such as some regions of southern Spain and southern Italy, as well as some European Nordic regions of Sweden and Finland.

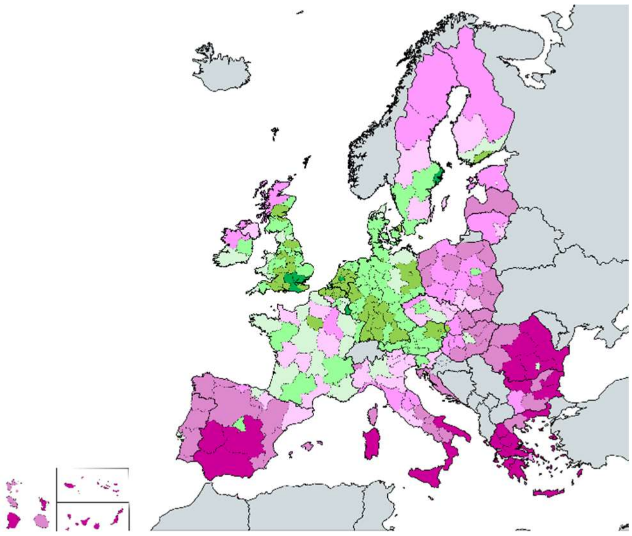
In the European map of the Mahalanobis ranking the effect of correlations on the clusters is more evident. In fact, the map presents the greatest dissimilarities compared to the map of the RCI. On the one hand, we observe a general improvement in the competitiveness level of some regions of southern countries, for instance, regions in central-northern Greece, some regions of central and eastern European countries of Poland, Hungary, Slovakia and some regions of central European countries such as France and Austria. On the other hand, some top-competitive regions in the RCI are placed in a lower competitive cluster, such as some regions of northern European countries of Finland, Sweden (including Stockholm, which is the most competitive region in the RCI), middle-ranking regions of Ireland and northern Scotland, as well as some regions of central European countries like eastern Germany and northern Denmark. This result highlights the effect of the correlations of the RCI pillars on the final ranking of regions.



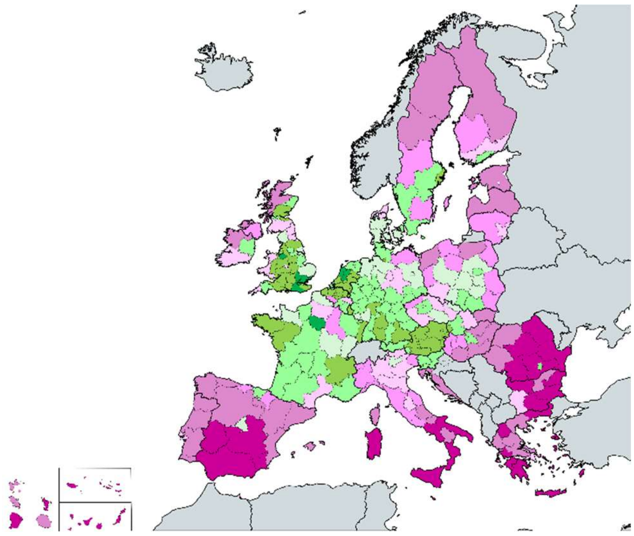

Map of the RCI (source Annoni & Dijkstra, 2019 p. 6)



Map of the Manhattan ranking



Map of the Euclidean Ranking



Map of the Mahalanobis ranking

**Legend: Cluster of competitiveness**

- Cluster 1 - Most competitive
- Cluster 2 - Highly competitive
- Cluster 3 - Fairly competitive
- Cluster 4 - Slightly competitive
- Cluster 5 - Competitive
- Cluster 6 - Not very competitive
- Cluster 7 - Hardly competitive
- Cluster 8 - Not competitive at all

Figure 3: European maps of the RCI and of the TOPSIS rankings

A detailed inspection derived from Table 5 (further details available on request) highlights the fact that in the RCI there are some regions that maintain their level of competitiveness across rankings since they maintain the membership of the same cluster across the overall analysis, especially those that belong to overperforming and underperforming clusters, while other regions do not, since they are sensitive to the distance measure used, particularly those with a medium level of competitiveness.

For instance, some top-competitive regions of the RCI, such as Inner London, Surrey or Utrecht, as well as some highly competitive regions of the Netherlands or Belgium, maintain their membership to the top-performing clusters throughout the analysis. This is an interesting finding since their competitiveness level does not depend on the distance measure used. Hence, as stated in Section 4.1, this might be related to the fact that according to some authors (Bartkowska & Riedl, 2012; Corrado, Martin, & Weeks, 2005; Galor, 1996), territories may converge on a development equilibrium, which depends on their initial structural characteristics and socio-economic situations, as well as effective regional policy planning. Moreover, according to Fagerberg & Srholec (2017) the competitiveness level of a region depends on its ability to maintain or increase its living standard. Therefore, it is possible that these top-competitive regions are more capable of maintaining a high competitiveness level compared to other regions.

At the same time, we observe an opposite situation for some regions belonging to underperforming clusters. For instance, some of the outermost regions of southern Italy, as well as regions of southern Greece, Eastern Romania and Bulgaria show a low competitive profile across the overall analysis. This may depend on their regional endogenous characteristics (Bartkowska & Riedl, 2012) as well as on weaknesses in their policy planning. This is in line with Annoni & Dijkstra, (2019) who argue that in Europe disparities in regional development are still present, especially for the outermost regions since they have specific characteristics that exclude them from spillover effects from other more advanced regions. At the same time, even though many of these regions are characterised by a good performance in some pillars, these are not sufficient for a general improvement in their level of competitiveness.

Regions in the central clusters (fairly competitive, slightly competitive, competitive, not very competitive) are more difficult to ascertain. First of all, this finding suggests that regions in the central clusters are difficult to categorize unequivocally within a specific level of competitiveness. Second, these regions seem to be in transition toward a higher or lower cluster (Bartkowska & Riedl, 2012) since it is assumed that regions move along a different development path due to changes in their economic conditions (Annoni & Dijkstra, 2019).

| Cluster / Regions | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Overall index |
|---|---|---|---|---|---|---|---|---|---|
| Same cluster membership across rankings (%) | 50.00% | 50,00% | 45,16% | 7,69% | 25,00% | 33,33% | 56,82% | 72,73% | 44.40% |
| Different cluster membership across rankings (%) | 50.00% | 50,00% | 54,84% | 92,31% | 75,00% | 66,67% | 43,18% | 27,27% | 55.60% |
| **Total** | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% |

Table 5: % of regions in each cluster that maintain (and do not maintain) the same cluster membership across rankings

The analysis highlights a complex situation in Europe, which exhibits great differences and disparities (Borsekova, Korony, & Nijkamp, 2021b; Ertur, Le Gallo, and Baumont 2006; European Union, 2017a; European Union, 2011; Rizzi, Graziano, & Dallara, 2018). Our results are in line with evidence provided by other authors: Camagni & Capello (2013); Lengyel & Rechnitzer (2013); Möbius & Althammer (2020), who argue that growth across regions is uneven, as regions give different importance and adopt different strategies for territorial growth (Annoni et al., 2016). We also agree with Niebuhr & Stiller (2003), since in Europe one single development pattern does not exist: certain top competitive regions suffer from instability, whereas certain less competitive regions are more dynamic, and their competitiveness level needs to be reconsidered. However, this analysis is not intended to address the issue of prosperous regions and lagging regions, or spatial planning, since this matter has already been investigated (Evers, 2008; Möbius & Althammer, 2020; Niebuhr & Stiller, 2003). It just offers another perspective on regional competitiveness in Europe that might turn out to be beneficial when assessing regional development since regional growth is affected by different factors, depending on the development stage (Annoni, De Dominicisi, & Khabirpouri, 2019).

The analysis reveals that the measurement of competitiveness at regional level is difficult to determine in a definitive manner (Kresl & Singh, 1999) since different methodologies can lead to different results. However, the present study provides evidence that TOPSIS is a useful method for measuring regional competitiveness. Moreover, it underlines that it is essential to take into account correlations when measuring regional competitiveness since competitiveness is a multidimensional and intertwined concept (Annoni & Dijkstra, 2019), driven by interrelated factors (Cheng, Long, Chen & Li, 2018; Pike et al., 2016; Wang & Wang, 2014). Finally, the comparison of TOPSIS rankings by using different distance measures provides insights that are not evident using a single distance measure, which might be helpful in the design of the necessary reforms to promote regional competitiveness (Annoni & Dijkstra, 2019).

## 5. Concluding remarks, limitations and future research

This paper proposed a comparative analysis to assess regional competitiveness of European regions at NUTS 2 level based on the Technique for Order Preference by Similarity to Ideal Solution. Using data from the EU Regional Competitiveness Index 2019, the paper explored the use of the TOPSIS method based on three different distance measures, i.e. the Manhattan, Euclidean and Mahalanobis distance measures, taking the RCI as the reference of the analysis. The results are three rankings of regions that are compared to the RCI by considering both rankings and clusters, leading to three considerations.

First, the most important insight concerns the connection between the TOPSIS method and the RCI methodology. We find that the RCI coincides with the TOPSIS ranking based on the Manhattan distance measure, confirming the suitability of the RCI as the reference of the study and providing a bridge between the two approaches. Moreover, the finding suggests the appropriateness of the TOPSIS method in the measurement of regional competitiveness.

Second, since the pillars of the RCI are closely correlated, the TOPSIS ranking based on the Mahalanobis distance measure is the ranking that presents the greatest dissimilarity in the final ranking of regions compared to the RCI. Therefore, this result confirms the insights from previous studies, namely that regional competitiveness is driven by interrelated and intertwined factors (Aiginger & Firgo, 2017; Franco et al., 2014; Pike et al., 2016; Wang & Wang, 2014). Thus, when measuring regional competitiveness, correlations between indicators should be taken into account since the various aspects of competitiveness influence each other, and overlooking correlations would cause certain factors to be overweighted (Annoni & Dijkstra, 2019; Huovari et al., 2002). In addition, taking correlations into account helps to properly reflect the characteristics of the territories analysed (Wang & Wang, 2014).

Third, by keeping the same cardinality of the clusters of the RCI in the TOPSIS rankings, it is possible to examine how the composition of the clusters of the RCI is altered when the TOPSIS method is applied. It was found that clusters did not alter their composition in the Manhattan ranking, while they did in the Euclidean and Mahalanobis rankings. Regions that move from one cluster to another also change their competitiveness level with respect to the ranking under consideration. In particular, in the Mahalanobis ranking, the effect that correlations have on clusters is more evident since they present the greatest variation in their composition. A detailed inspection of the results shows that in the RCI there are some regions with a stable competitiveness level across rankings since they maintain membership of the same cluster across the overall analysis, especially those regions belonging to the overperforming and underperforming clusters, while other regions do not, particularly those belonging to the middle-ranking clusters. The fact that some regions are less sensitive to the choice of distance measure might be attributed to the fact that according to the literature, regions may converge on a development equilibrium, depending on their initial structural characteristics and socio-economic conditions (Bartkowska & Riedl, 2012; Corrado et al., 2005; Galor, 1996). At the same time, regions that are more sensitive to the distance measure used are more difficult to classify unambiguously within a specific level of competitiveness, hence, drawing on the findings of Bartkowska & Riedl (2012), these regions seem to be in transition toward a lower or higher cluster since regions move along different development paths due to changes in economic conditions (Annoni & Dijkstra, 2019). Our findings are in line with the results provided by other authors (Borsekova et al., 2021b; Önsel, et al., 2008; Ülengin et al., 2002), who underline a heterogeneous and uneven situation in Europe (European Union, 2017b; Möbius & Althammer, 2020).

Since regional competitiveness is a complex concept that is difficult to measure accurately (Huggins et al., 2014), the current analysis presents further insights complementing the literature (Huggins, 2003; Lengyel & Rechnitzer, 2013). Moreover, it also tries to overcome the weaknesses arising from the use of a single index, as highlighted by other scholars (Bristow, 2010a). The use of the TOPSIS method with the application of different distance measures helps to provide insights that are not evident through the use of a single distance measure, which inevitably only provides a single take on such a complex matter. In particular, the present analysis reveals, on the one hand, that TOPSIS is a proper method for measuring regional competitiveness, while on the other hand, it shows that correlations should be taken into account when measuring regional competitiveness. Therefore, we suggest considering the clusters of the Mahalanobis ranking as a good starting point for future research.

The present analysis considers cross-section data, which provide only an image of the regional competitive situation in Europe. However, when investigating regional competitiveness or territorial disparities, scholars opt for time-series data (Bartkowska & Riedl, 2012; Bosker, 2009; Ertur et al., 2006). Therefore, as a further step of this analysis it might be interesting to replicate it on a different point in time, by examining the RCI from 2010 to 2019 in order to investigate how the rankings of regions and the composition of clusters change over time.

## Author statement

**Filippo Ferrarini**: Conceptualization, Data processing, Formal analysis, Investigation, Writing of first draft, Visualization; **Silvia Muzzioli**: Conceptualization, Project Administration, Supervision, Writing review & Editing; **Bernard De Baets**: Methodology, Supervision, Validation, Writing review & Editing.

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## Annex

Annex A: Position of the European regions in the different ranking (RCI as reference)

| Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking | Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking |
|---|---|---|---|---|---|---|---|
| Stockholm | 1 | 5 | 13 | Antwerpen | 30 | 27 | 20 |
| Inner London & other | 2 | 2 | 1 | Oost-Vlaanderen | 31 | 24 | 17 |
| Utrecht | 3 | 4 | 3 | Berlin & other | 32 | 34 | 114 |
| Berkshire & other | 4 | 3 | 18 | Overijssel | 33 | 48 | 40 |
| Surrey & other | 5 | 1 | 2 | Östra Mellansverige | 34 | 78 | 100 |
| Hovedstaden | 6 | 12 | 57 | Västsverige | 35 | 76 | 103 |
| Luxembourg | 7 | 6 | 9 | Herefordshire & other | 36 | 32 | 39 |
| Oberbayern | 8 | 8 | 32 | North Yorkshire | 37 | 29 | 12 |
| Flevoland & other | 9 | 9 | 6 | Freiburg | 38 | 37 | 83 |
| Helsinki | 10 | 21 | 76 | Rheinhessen-Pfalz | 39 | 41 | 129 |
| Île de France | 11 | 7 | 4 | Gießen | 40 | 36 | 59 |
| Hamburg | 12 | 13 | 41 | Leicestershire & other | 41 | 31 | 21 |
| Darmstadt | 13 | 14 | 33 | Düsseldorf | 42 | 45 | 70 |
| Zuid-Holland | 14 | 18 | 14 | Gr Manchst. | 43 | 30 | 16 |
| Hampshire & other | 15 | 11 | 11 | Groningen | 44 | 65 | 85 |
| Karlsruhe | 16 | 17 | 68 | Unterfranken | 45 | 43 | 53 |
| Cheshire | 17 | 10 | 5 | Schwaben | 46 | 49 | 49 |
| Stuttgart | 18 | 19 | 36 | Münster | 47 | 53 | 74 |
| Köln | 19 | 20 | 51 | Midtjylland | 48 | 95 | 125 |
| Noord-Brabant | 20 | 25 | 19 | Braunschweig | 49 | 54 | 153 |
| Gelderland | 21 | 28 | 26 | Sjælland | 50 | 92 | 115 |
| Gloucestershire & other | 22 | 15 | 10 | Leipzig | 51 | 47 | 52 |
| Tübingen | 23 | 23 | 43 | Eastern Scotland | 52 | 46 | 46 |
| Sydsverige | 24 | 50 | 62 | Derbs. & other | 53 | 39 | 44 |
| Bruxelles & other | 25 | 16 | 7 | Bremen | 54 | 60 | 136 |
| Kent | 26 | 26 | 38 | Dorset & other | 55 | 40 | 22 |
| Limburg | 27 | 35 | 35 | Limburg | 56 | 44 | 23 |
| Mittelfranken | 28 | 33 | 97 | Hannover | 57 | 66 | 118 |
| Wien & other | 29 | 22 | 8 | Dresden | 58 | 59 | 75 |

Continued

| Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking | Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking |
|---|---|---|---|---|---|---|---|
| Zeeland | 59 | 83 | 64 | Lüneburg | 87 | 91 | 111 |
| East Anglia | 60 | 57 | 124 | Rhône-Alpes | 88 | 62 | 15 |
| Arnsberg | 61 | 70 | 90 | Burgenland | 89 | 74 | 28 |
| West Central Scotland | 62 | 51 | 58 | Thüringen | 90 | 88 | 82 |
| West-Vlaanderen | 63 | 42 | 25 | Tirol | 91 | 84 | 56 |
| Koblenz | 64 | 75 | 93 | Kassel | 92 | 87 | 86 |
| Oberpfalz | 65 | 69 | 101 | Chemnitz | 93 | 86 | 67 |
| Drenthe | 66 | 89 | 63 | Niederbayern | 94 | 96 | 98 |
| Bratislavský kraj | 67 | 38 | 24 | Devon | 95 | 94 | 78 |
| West Yorkshire | 68 | 52 | 55 | Saarland | 96 | 98 | 117 |
| Praha & other | 69 | 55 | 71 | West Midlands | 97 | 97 | 141 |
| Oberfranken | 70 | 68 | 66 | Etelä-Suomi | 98 | 124 | 147 |
| East Wales | 71 | 61 | 37 | Comunidad de Madrid | 99 | 93 | 131 |
| Schleswig-Holstein | 72 | 72 | 88 | Nordjylland | 100 | 126 | 156 |
| North Eastern Scotland | 73 | 79 | 110 | Kärnten | 101 | 99 | 47 |
| Oberösterreich | 74 | 63 | 34 | Weser-Ems | 102 | 104 | 121 |
| Vorarlberg | 75 | 73 | 61 | Alsace | 103 | 90 | 27 |
| Shropshire & other | 76 | 58 | 42 | Northumberland and other | 104 | 106 | 143 |
| Eastern and Midland | 77 | 82 | 94 | Warszawski stołeczny | 105 | 85 | 77 |
| Detmold | 78 | 81 | 89 | Southern Scotland | 106 | 107 | 138 |
| Merseyside | 79 | 67 | 80 | Midi-Pyrénées | 107 | 100 | 54 |
| Lancashire | 80 | 56 | 31 | Sachsen-Anhalt | 108 | 113 | 154 |
| Syddanmark | 81 | 103 | 132 | Zahodna Slovenija | 109 | 105 | 92 |
| Steiermark | 82 | 71 | 45 | Småland med öarna | 110 | 139 | 165 |
| Salzburg | 83 | 77 | 48 | Länsi-Suomi | 111 | 143 | 174 |
| South Yorkshire | 84 | 64 | 50 | East Yorkshire & other | 112 | 109 | 123 |
| Trier | 85 | 80 | 73 | Cumbria | 113 | 111 | 134 |
| Friesland | 86 | 101 | 102 | Pays de la Loire | 114 | 102 | 30 |

Continued

| Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking | Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking |
|---|---|---|---|---|---|---|---|
| Mecklenburg-Vorpommern | 115 | 125 | 170 | Bourgogne | 143 | 142 | 120 |
| Lincolnshire | 116 | 108 | 95 | Åland | 144 | 177 | 196 |
| Southern | 117 | 130 | 150 | Pohjois- ja Itä-Suomi | 145 | 186 | 208 |
| Tees Valley & other | 118 | 116 | 152 | Lombardia | 146 | 136 | 155 |
| Cornwall & other | 119 | 129 | 146 | Highlands & other | 147 | 165 | 194 |
| Namur | 120 | 110 | 105 | Languedoc-Roussillon | 148 | 152 | 161 |
| Provence-Alpes-Côte d'Azur | 121 | 115 | 96 | Limousin | 149 | 144 | 99 |
| Aquitaine | 122 | 119 | 65 | Severovýchod | 150 | 148 | 139 |
| Bretagne | 123 | 112 | 29 | Bucureşti - Ilfov | 151 | 118 | 84 |
| Liège | 124 | 123 | 159 | Basse-Normandie | 152 | 145 | 116 |
| País Vasco | 125 | 114 | 91 | Poitou-Charentes | 153 | 149 | 104 |
| Centre - Val de Loire | 126 | 117 | 72 | Moravskoslezsko | 154 | 150 | 126 |
| West Wales & other | 127 | 131 | 148 | Vzhodna Slovenija | 155 | 155 | 109 |
| Área Metr. de Lisboa | 128 | 121 | 144 | Střední Morava | 156 | 154 | 137 |
| Haute-Normandie | 129 | 122 | 79 | Provincia Aut. Trento | 157 | 140 | 119 |
| Norra Mellansverige | 130 | 160 | 190 | Jihozápad | 158 | 156 | 162 |
| Jihovýchod | 131 | 132 | 127 | Eesti | 159 | 179 | 209 |
| Lorraine | 132 | 127 | 69 | Sostinės regionas | 160 | 151 | 164 |
| Northern Ireland | 133 | 141 | 180 | Cataluña | 161 | 163 | 201 |
| Luxembourg | 134 | 128 | 107 | Emilia-Romagna | 162 | 146 | 160 |
| Övre Norrland | 135 | 182 | 217 | Lazio | 163 | 153 | 177 |
| Auvergne | 136 | 133 | 87 | Northern and Western | 164 | 175 | 192 |
| Nord-Pas de Calais | 137 | 135 | 122 | Comunidad Foral de Navarra | 165 | 162 | 173 |
| Hainaut | 138 | 138 | 182 | Champagne-Ardenne | 166 | 170 | 188 |
| Picardie | 139 | 137 | 140 | Piemonte | 167 | 159 | 181 |
| Közép-Magy. | 140 | 120 | 106 | Veneto | 168 | 158 | 157 |
| Franche-Comté | 141 | 134 | 112 | Friuli-V. Giulia | 169 | 161 | 167 |
| Mellersta Norrland | 142 | 185 | 211 | Śląskie | 170 | 147 | 60 |

Continued

| Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking | Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking |
|---|---|---|---|---|---|---|---|
| Kýpros | 171 | 176 | 166 | Opolskie | 201 | 189 | 128 |
| Liguria | 172 | 168 | 187 | Latvija | 202 | 209 | 206 |
| Toscana | 173 | 166 | 171 | Norte | 203 | 211 | 225 |
| Cantabria | 174 | 188 | 189 | Martinique | 204 | 205 | 205 |
| Małopolskie | 175 | 157 | 81 | Castilla y León | 205 | 217 | 226 |
| Prov. Aut. Bolz. | 176 | 164 | 145 | Illes Balears | 206 | 216 | 234 |
| Malta | 177 | 199 | 247 | Zachodniopomorskie | 207 | 202 | 193 |
| Severozápad | 178 | 180 | 186 | Podkarpackie | 208 | 201 | 169 |
| Západné Slovensko | 179 | 172 | 108 | Lubelskie | 209 | 197 | 168 |
| Attiki | 180 | 169 | 142 | Kujawsko-pomorskie | 210 | 198 | 176 |
| Yugozapaden | 181 | 167 | 163 | Podlaskie | 211 | 207 | 185 |
| Pomorskie | 182 | 178 | 172 | Świętokrzyskie | 212 | 194 | 130 |
| Dolnośląskie | 183 | 171 | 149 | Lubuskie | 213 | 196 | 178 |
| Umbria | 184 | 181 | 151 | Abruzzo | 214 | 214 | 207 |
| Corse | 185 | 200 | 212 | Molise | 215 | 212 | 200 |
| Principado de Asturias | 186 | 195 | 198 | Kontinentalna Hrvatska | 216 | 215 | 195 |
| Mazowiecki regionalny | 187 | 173 | 113 | La Réunion | 217 | 219 | 227 |
| Aragón | 188 | 210 | 230 | Východné Slovensko | 218 | 218 | 199 |
| Marche | 189 | 190 | 179 | Región de Murcia | 219 | 230 | 248 |
| Łódzkie | 190 | 174 | 133 | Algarve | 220 | 226 | 221 |
| Vidurio vakarų Lietuv. | 191 | 191 | 184 | Dél-Alföld | 221 | 213 | 203 |
| Comunidad Valenciana | 192 | 206 | 216 | Jadranska Hrvatska | 222 | 221 | 197 |
| La Rioja | 193 | 204 | 204 | Alentejo | 223 | 225 | 233 |
| Wielkopolskie | 194 | 184 | 135 | Castilla-La Mancha | 224 | 236 | 255 |
| Közép-Dunántúl | 195 | 183 | 175 | Warmińsko-mazurskie | 225 | 223 | 210 |
| Nyugat-Dunántúl | 196 | 187 | 183 | Guadeloupe | 226 | 227 | 229 |
| Galicia | 197 | 208 | 213 | Andalucía | 227 | 239 | 257 |
| Centro | 198 | 203 | 214 | Észak-Magyarország | 228 | 220 | 220 |
| Stredné Slovensko | 199 | 193 | 158 | Canarias | 229 | 241 | 246 |
| Valle d'Aosta | 200 | 192 | 191 | Dél-Dunántúl | 230 | 222 | 219 |

Continued

| Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking | Regions | RCI and Manhattan ranking | Euclidean ranking | Mahalanobis ranking |
|---|---|---|---|---|---|---|---|
| Basilicata | 231 | 232 | 231 | Ciudad Aut. Melilla | 261 | 266 | 266 |
| Campania | 232 | 229 | 242 | Dytiki Ellada | 262 | 262 | 249 |
| Észak-Alföld | 233 | 224 | 218 | Dytiki Makedonia | 263 | 260 | 238 |
| Sardegna | 234 | 243 | 259 | Mayotte | 264 | 267 | 268 |
| Puglia | 235 | 240 | 251 | Anatoliki Makedonia, Thraki | 265 | 264 | 254 |
| Região Aut. da Madeira | 236 | 244 | 256 | Guyane | 266 | 265 | 267 |
| Yuzhen tsentralen | 237 | 233 | 239 | Sud-Est | 267 | 256 | 260 |
| Vest | 238 | 228 | 215 | Voreio Aigaio | 268 | 268 | 264 |
| Kentriki Makedonia | 239 | 235 | 202 | | | | |
| Severoiztochen | 240 | 237 | 236 | | | | |
| Severen tsentralen | 241 | 234 | 232 | | | | |
| Sicilia | 242 | 247 | 262 | | | | |
| Extremadura | 243 | 258 | 265 | | | | |
| Calabria | 244 | 249 | 253 | | | | |
| Ciudad Aut. de Ceuta | 245 | 254 | 258 | | | | |
| Nord-Vest | 246 | 231 | 222 | | | | |
| Sud - Muntenia | 247 | 238 | 237 | | | | |
| Yugoiztochen | 248 | 245 | 250 | | | | |
| Centru | 249 | 242 | 240 | | | | |
| Kriti | 250 | 253 | 244 | | | | |
| Ipeiros | 251 | 250 | 224 | | | | |
| Thessalia | 252 | 252 | 223 | | | | |
| Região Aut. dos Açores | 253 | 263 | 263 | | | | |
| Sud-Vest Oltenia | 254 | 248 | 245 | | | | |
| Sterea Ellada | 255 | 251 | 228 | | | | |
| Ionia Nisia | 256 | 257 | 235 | | | | |
| Nord-Est | 257 | 246 | 252 | | | | |
| Peloponnisos | 258 | 259 | 241 | | | | |
| Notio Aigaio | 259 | 261 | 243 | | | | |
| Severozapaden | 260 | 255 | 261 | | | | |