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A TOPSIS analysis of regional competitiveness at European level

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Abstract

Purpose – The measurement of regional competitiveness is becoming essential for policymakers to address territorial disparities, while considering the issue of correlations among indicators. Therefore, the purpose of this paper is to measure regional competitiveness using the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) by considering different distance measures and two levels of analysis to provide a comparative and comprehensive measurement of regional competitiveness in Europe.

Design/methodology/approach – The authors apply TOPSIS based on three different distance measures (the Manhattan, the Euclidean and the Mahalanobis distance measures) to the regions of the EU Regional Competitiveness Index (RCI) 2019, which is taken as the frame of reference.

Findings – The authors replicate the RCI by using TOPSIS with a less preferred choice of distance measure, indicating TOPSIS as a valuable method for policymakers in the analysis of regional competitiveness. The authors argue in favour of the Mahalanobis distance measure as the best of the three, as it considers correlations among macro-economic indicators.

Originality/value – This study aims to make three contributions. Firstly, by replicating the RCI by means of TOPSIS with a less preferred choice of distance measure, the paper provides a benchmark for future research on regional competitiveness. Secondly, by suggesting the use of TOPSIS with the use of the Mahalanobis distance measure, the authors show how to measure regional competitiveness by taking into account correlations among pillars. Thirdly, the authors argue in favour of considering clusters of regions when measuring regional competitiveness.

Keywords TOPSIS, Regional competitiveness, Mahalanobis distance measure, RCI, European Union

Paper type Research paper

1. Introduction

The level of development of the various regions of the European Union (EU) is highly uneven, with some capital regions experiencing significant levels of growth and peripheral ones

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struggling to improve. In this connection, the measurement of regional competitiveness is becoming essential for policymakers, since it is one of the major levers for economic progress (Moirangthem and Nag, 2022). Researchers have underlined the need to further investigate the competitiveness of regions, taking account of the fact that country indices fail to cast light on subnational trends and performance gaps across nations (Dagilienė *et al.*, 2020; Huggins *et al.*, 2013). Various approaches have been adopted to measure regional competitiveness. The construction of composite indices, with the combination of several independent dimensions examining a specific facet of the regional economy, is the predominant approach adopted (Annoni *et al.*, 2016; Bristow, 2010; Moirangthem and Nag, 2022).

It is frequently argued that the dimensions of regional competitiveness are not independent (Cheng *et al.*, 2018; Dagilienė *et al.*, 2020). In fact, macroeconomic dimensions are tightly intertwined, and scholars underline how correlations need to be taken into account to provide an accurate measurement of regional development (Huovari *et al.*, 2002; Pontarollo and Serpieri, 2021; Reyes and Useche, 2019). For instance, Franco *et al.* (2014) in their European Commission report, argue that competitiveness indicators such as productivity, employment growth or labour force participation are closely correlated with each other. Similarly, Cheng *et al.* (2018), Wenzel and Wolf (2016) and Wang and Wang (2014), in their analysis of macroeconomic indicators, show that they exhibit high correlation coefficients, with many above 0.95.

Therefore, the literature evidences how the aspect of correlation is in line with cumulative causation theory, according to which economic growth (even regional) is the result of a multi-causal approach where changes in any macroeconomic dimension will affect subsequent changes in other dimensions in a sort of self-reinforcing cumulative circle (Lehtonen and Tykkyläinen, 2018; Skott and Auerbach, 1995). As a result, to measure regional competitiveness accurately, the aspect of correlation should be taken into account, as overlooking it can lead to biased results.

Composite indices do not deal with correlations, thus causing factors to be overestimated or underestimated when ranking alternatives, leading to misleading measurements (Pérez-Moreno *et al.*, 2016; Wang and Wang, 2014). In this connection, Multiple Criteria Decision-Making (MCDM) methods can be considered as valuable alternative techniques in the measurement of regional competitiveness, as they can rank alternatives easily and assist policymakers in designing policy interventions (Bilbao-Terol *et al.*, 2019).

The *Technique for Order of Preference by Similarity to Ideal Solution* (TOPSIS) (Hwang and Yoon, 1981) is one of the most widely used MCDM methods in many fields such as human resource management, water management or supply chain management due to its ability to help decision-makers to solve real-life problems and to rank alternatives (Behzadian *et al.*, 2012). The basic idea underlying TOPSIS is to rank alternatives on the basis of the ratio of the distance from a positive ideal solution to the distance from a negative ideal solution.

TOPSIS is an ideal MCDM method for the measurement of regional competitiveness, because it can deal with the aspect of correlation, thus providing a more accurate measurement of competitiveness, aligning it to the underlying cumulative causation theory. At the same time, it can use weights that are obtained objectively from macroeconomic variables, such as gross domestic product (GDP), in the same way as classical composite indicators, while other methods such as Decision Making Trial and Evaluation Laboratory (DEMATEL) or Analytic Network Process (ANP) are less effective in this regard. However, the application of TOPSIS in this field has been largely overlooked and only a few studies are to be found in the literature. Moreover, existing contributions usually consider only the aspect of rankings (Qian *et al.*, 2019), and overlook the aspect of the clusters of competitiveness. In this extent, clusters refer to groups of regions with similar structural characteristics, and similar levels of competitiveness. Considering the aspect of clusters of regions is important because they provide much more information about territorial disparities, rather than simply looking at rankings, as proposed by a number of scholars (Annoni and Dijkstra, 2019; Beltran *et al.*, 2024).

Therefore, these issues lead to the following questions:

Q1. Is TOPSIS a valuable method for measuring regional competitiveness?

Q2. Is it important to consider correlations when measuring regional competitiveness?

Q3. Is it important to consider not only the aspect of rankings, but also the clusters of competitiveness when measuring the level of competitiveness of regions?

To address these questions, the present study applies TOPSIS to the regions of the EU Regional Competitiveness Index (RCI) 2019, taken as the frame of reference. The RCI is the main composite index of regional competitiveness at the EU level; it measures regional competitiveness of 268 territories at NUTS 2 regional level (Nomenclature of Units for Territorial Statistics) considering 74 indicators, grouped into 11 independent pillars. Various researchers have used it as a fundamental frame of reference for the analysis of regional development (Bilbao-Terol *et al.*, 2019; Bocci *et al.*, 2022; Borsekova *et al.*, 2021b). Consequently, the present study takes the RCI as the frame of reference as it overlooks the issue of correlation, and it clusters regions on the basis of their level of competitiveness. Thus, it is a good basis to address these research questions.

In this study, we apply three different distance measures, namely, the Manhattan, Euclidean and Mahalanobis distance measures. The use of different distance measures on a large number of regions provides a broad application of TOPSIS to cast light on which of the distance measures should be used for the measurement of regional competitiveness, since they have different properties (Chang *et al.*, 2010). Moreover, as two levels of analysis are considered, one based on rankings and the other based on clusters of competitiveness, this study facilitates a comprehensive measurement as rankings are highly sensitive to the distance measure used, while clusters are less so. In fact, regions can easily change their position in rankings, as the variation of even one dimension or calculation method is sufficient to cause a region to shift from its initial position to another one (Ivanová and Čepel, 2018; Pérez-Moreno *et al.*, 2016; Scaccabarozzi *et al.*, 2024). However, the analysis of clusters of competitiveness is more robust, as regions have more room for moving around within the cluster without changing their ranking in terms of competitiveness defined by the cluster itself (Annoni and Dijkstra, 2019; Beltran *et al.*, 2024).

This study aims to contribute to the measurement of regional competitiveness in three different ways. Firstly, as the RCI is replicated by means of TOPSIS with a less preferred choice of distance measure, this study aims to provide a benchmark for future research into both regional competitiveness and TOPSIS applications as TOPSIS is indicated as a valid alternative method for the measurement of regional competitiveness. Secondly, the TOPSIS ranking based on the Mahalanobis distance measure provides the most robust results with respect to the other two distance measures, as it presents the lowest fluctuation in the closeness coefficient when robustness checks are applied. Hence, the study argues in favour of the Mahalanobis distance measure as the best distance measure to be applied in the measurement of regional competitiveness, underscoring the need to consider the aspect of correlations. Thirdly, the study highlights the need to consider the aspect of clusters of regions in competitiveness measurement as it provides a broader picture of regional competitiveness levels. Unlike previous studies, TOPSIS is applied to 268 European regions, demonstrating the ability of TOPSIS to rank a large number of regions.

This paper proceeds as follows. Section 2 provides a literature review on regional competitiveness in the EU and approaches to its measurement. Section 3 provides an outline of the methodology, whereas Section 4 summarizes the results of the analysis, focusing on rankings (Subsection 4.1) and clusters (Subsection 4.2). Section 5 consists of concluding remarks, policy suggestions and comments on the limitations of the study.

2. Literature review

Defining territorial competitiveness is problematic, controversial and far from being comprehensively understood. It is a matter of common observation that the socio-economic regional development is still heterogeneous and uneven in Europe (e.g. Borsekova *et al.*, 2021b). Since the economic crisis of 2008, Europe has adopted a wide range of policy actions to improve the economic development of the European Member States. Nevertheless, not all regions have the same resilience, hence, disparities in regional development and competitiveness persist (Annoni and Dijkstra, 2019; Dagilienė *et al.*, 2020; Moirangthem and Nag, 2022; Pontarollo and Serpieri, 2020). Möbius and Althammer (2020), in their spatial econometric analysis of sustainable competitiveness of European regions, found that northern EU regions tend to perform better on sustainable competitiveness than southern regions, while other scholars such as Borsekova *et al.* (2021b) argue that in Europe regional disparities persist, particularly because post-socialist regions are less developed with respect to the liberal market economy/central regions. Some strong liberal market economy regions perform particularly well on all indicators due to their economic links with the rest of Europe, while many mid-ranking competitive regions do not benefit from the same advantages. Several peripheral regions struggle to take advantage of spill-over effects due to their geographical location and structural weaknesses (Annoni and Dijkstra, 2019). In this framework, the measurement of regional competitiveness is becoming essential to promote policy actions for addressing regional disparities.

One of the most common approaches to the measurement of regional competitiveness consists of the construction of a composite index, with the combination of several indicators examining a specific facet of the regional economy. At country level, many studies are available. For instance, Huggins *et al.* (2021) have constructed an index for measuring the competitiveness level of UK regions, while Bronisz *et al.* (2008) have designed a composite index for measuring the competitiveness of Polish regions.

Nevertheless, these kinds of indices often overlook the issue of correlation, with the risk of underestimating or overestimating factors. In this connection, cumulative causation theory states that economic growth follows a self-reinforcing process, in which regional dimensions are reinforced by other dimensions. Positive (or negative) changes of one dimension will affect changes in other dimensions as a result of localized effects of returns (Lehtonen and Tykkyläinen, 2018; Martin, 2016; Skott and Auerbach, 1995). Therefore, "regional development is subject to cumulative causation, since subregions that have a high value for one sub-index also tend to have high values for other sub-indices" (Huovari *et al.*, 2002, p. 11). Consequently, high performing regions can benefit from virtuous circles of economic growth, while low performing regions can find themselves in a vicious circle of underdevelopment (Tervo, 2005). As highlighted above, the aspect of correlation is critical in the measurement of regional competitiveness since macroeconomic dimensions tend to reinforce each other (Pike *et al.*, 2016).

Along this veing, MCDM methods are a valuable alternative in the measurement of regional competitiveness as they can assist policymakers in sorting and ranking alternatives to make faster and easier decisions (Fernandez *et al.*, 2013). Among the several MCDM methods in the literature, such as DEMATEL, Elimination and Choice Expressing Reality

(ELECTRE) or ANP, which have been mainly adopted for the solution of real-life problems (i.e. environmental management or supply chain management) (Mardani *et al.*, 2015), TOPSIS proved to be an appropriate method for determining the ranking of European territories when considering macroeconomic indicators (Ardelli, 2019). In particular, Balcerzak and Pietrzak (2016) applied TOPSIS to measure the sustainable development of 24 European countries, resulting in a ranking that shows that northern countries tend to be the leaders in sustainable development. Similarly, Dinçer (2011) measured the European Union Member States on five macroeconomic criteria by means of TOPSIS, whereas Ture *et al.* (2019) assessed the Euro 2020 Strategy of 27 EU Member States with TOPSIS. Moreover, another advantage of TOPSIS with respect to other MCDM methods is that it can easily take into account the issue of correlation, providing a more accurate measurement of regional development. In addition, with TOPSIS it is possible to use the same weighting scheme used by composite indices, facilitating the comparison of the results.

Therefore, this study aims to measure the competitiveness level of European regions by taking as a frame of reference the RCI 2019. The RCI is the main periodic study of regional competitiveness in Europe, providing a comparable and multifaceted overview of the level of competitiveness of 268 territories at NUTS 2 regional level. The framework consists of 11 pillars covering various aspects of competitiveness (i.e. macroeconomic stability, labour market efficiency and technological readiness) grouped into three nested macrodimensions: the basic dimension, the efficiency dimension and the innovation dimension. The structure of the RCI is depicted in Figure 1. The index is computed as a weighted average, with the weights related to the different stages of the development of regions (see Annoni and Kozovska, 2010 for the full methodology). A number of scholars have adopted the RCI as the basis of their analysis of regional competitiveness: Bocci *et al.* (2022) used the data of the RCI to analyse the main drivers of regional competitiveness using a Regression Tree

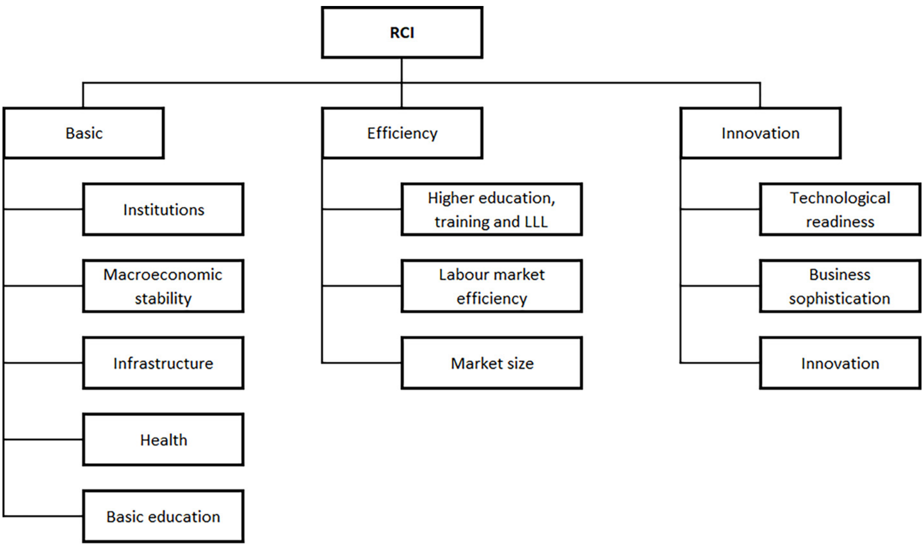

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Figure 1. The RCI with the three dimensions and the eleven pillars

analysis, whereas Borsekova *et al.* (2021b) used the RCI to measure regional socio-economic cohesion in Europe. However, none of these studies applied TOPSIS for the analysis of regional competitiveness.

The present study seeks to contribute to the scholarly discussion by offering a valid reference point for future research on regional competitiveness through the application of MCDM methods.

3. Data and methods

The data for this study comes from the 11 pillars depicted in Figure 1 for the 268 European regions and of the RCI (2019), retrieved from the website of the European Union (European Union, 2019). This website provides the final aggregated data of the 11 pillars, derived from a set of 84 indicators spanning the period 2015–2017, selected by the European Union in line with the literature and using national, subnational (i.e. World Bank, Eurostat) or regional statistics. For instance, for the institution pillar, indicators such as the corruption or political stability index were selected, whereas macroeconomic stability is based on statistics such as national savings or private-sector debt. Infrastructure consists of data such as the percentage of the population with access to rail services or the number of passengers per flight; health includes the number of road fatalities and the infant mortality rate. Basic education and higher education comprise the percentage of the population with access to information on education or the percentage of the regional population with access to university education. Labour market efficiency and market size pillars comprise indicators such as the percentage of individuals aged 15–64 in employment, and net disposable household income. Finally, the technological readiness, business sophistication and innovation pillars include indicators such as the percentage of households with access to internet, the number of organizations implementing organizational innovation and the number of scientific publications per million inhabitants.

The indicators belonging to each pillar were then standardized and finally aggregated as an arithmetic mean. Each of the indicators represents a dimension (pillar) used in the TOPSIS analysis, which was already available as aggregated outcome [1].

TOPSIS consists of five different steps (Kuo, 2017), which are outlined below. The first step involves the standardization of the data. Standardized z-scores of the 11 pillars that compose the index were used (see Figure 1), which were already available on the website. This initial data had undergone an aggregation and validation process by the European Union [i.e. sensitivity analysis, skewness analysis, principal component analysis and reverse coding to obtain the same positive impact on the final score, see Annoni and Kozovska (2010) for further details].

The second step involves weighting the 11 pillars. For the sake of comparison [2], the weighting scheme of the RCI was used (see Annoni and Dijkstra, 2019), which depends on regional GDP levels. This makes it possible to obtain a weighted normalized decision matrix V_{ij}, $i = 1, \ldots, 268$ and $j = 1, \ldots, 11$ with the input of the following steps.

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

The fourth step involves the computation for each region of the distance from the positive and negative ideal solution. To this end, the Manhattan, Euclidean and Mahalanobis distance measures are used to calculate the distance from the positive ideal solution (s_i^+) and the distance from the negative ideal solution (s_i^-) for each region a_i. The superscripts m, e and p are used for the Manhattan, Euclidean and Mahalanobis distance measures, respectively. For the Manhattan distance measure, we have:

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

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

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

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

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

The Euclidean distance measure 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 pillars. In fact, it weights the squared differences by the inverse of the covariance matrix ($\sum^{-1}$) and considers (T) the transposed vector of differences. Thus, if the pillars are not correlated, then the Mahalanobis distance measure coincides with the Euclidean distance measure.

It should be noted that both the Euclidean and Manhattan distance measure consider pillars as independent from each other, thus overlooking the aspect of inherent closeness among them. The Mahalanobis distance measure, instead, can control for inherent closeness, as it considers the inverse of the covariance matrix, which accounts for the covariances of the pillars considered, thereby their correlations coefficients.

Table 1 shows the first significant finding, as the pillars of the RCI are positively and significantly correlated among each other. For instance, looking at the institution pillar, it may be seen that it is highly correlated not only within pillars of its own sub-dimension (r = 0.5, p ≤ 0.01 on average), but also with pillars of other sub-dimensions such as technological readiness (r = 0.929, p ≤ 0.01) or innovation (r = 0.676, p ≤ 0.01). This is an important finding as it confirms that the determinants of regional competitiveness are interrelated, thus marked by cumulative causation (Pike *et al.*, 2016). Based on this finding, and considering the interdependent nature of the pillars, the Mahalanobis distance measure may be expected to be the most appropriate among the three used as it can account for the inherent closeness between pillars by considering their correlation.

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

			Basic				Efficiency			Innovation	
	1	2	3	4	5	6	7	8	9	10	11
1. Institutions	1.000										
2. Macroeconomic stability	0.575**	1.000									
3. Infrastructure	0.550**	0.292**	1.000								
4. Health	0.438**	−0.039	0.474**	1.000							
5. Basic education	0.716**	0.716**	0.442**	0.308**	1.000						
6. Higher education and LLL	0.642**	0.473**	0.327**	0.271**	0.457**	1.000					
7. Labor market efficiency	0.770**	0.683**	0.521**	0.291**	0.567**	0.652**	1.000				
8. Market size	0.473**	0.366**	0.809**	0.373**	0.348**	0.310**	0.636**	1.000			
9. Technological readiness	0.929**	0.552**	0.646**	0.484**	0.646**	0.588**	0.775**	0.603**	1.000		
10. Business sophistication	0.606**	0.235**	0.727**	0.460**	0.392**	0.458**	0.552**	0.729**	0.660**	1.000	
11. Innovation	0.676**	0.401**	0.686**	0.501**	0.459**	0.731**	0.734**	0.690**	0.724**	0.757**	1.000

Note: **Correlation is significant at the 0.01 level (2-tailed)
Source: Table by authors

The fifth step involves the computation of the relative closeness coefficients that constitute the final scores of the regions to obtain the final ranking. For each region a_i, the relative closeness coefficient C_i^* is computed as follows:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}. \quad (7)$$

This relative closeness coefficient belongs to the unit interval [0, 1]. 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, meaning that three different rankings are obtained according to the three distance measures used.

Finally, to compare the rankings obtained, two permutation metrics are used: the Kendall tau and the Spearman footrule. To facilitate the interpretation, the normalized Kendall tau K^* and the normalized Spearman footrule F^* (Beg Sufyan and Ahmad, 2003) are applied:

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

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

where σ^r and σ^p are the two rankings and n is the number of objects ranked.

If σ^r and σ^p are identical, then the value is 0, whereas if σ^r and σ^p are in the converse order, then the value is 1. The results of the rankings are examined in Section 4.1.

As a last step, to compare the results with the RCI, the clusters of competitiveness are analysed, and the results are shown in Section 4.2.

4. Discussion and findings

4.1 The RCI and the rankings obtained by TOPSIS

In this section, the results of the comparison of the Manhattan, Euclidean and Mahalanobis rankings with the RCI are presented. The Appendix Table A1 includes the three rankings for the first 50 regions of the RCI. Tables 2 and 3 present the matrices of the normalized Kendall tau K^* [equation (8)] and the normalized Spearman footrule F^* [equation (9)]. Both tables show that the Manhattan ranking perfectly replicates the RCI since all regions are in the same order. This makes it possible to take the RCI as the frame of reference for the analysis.

Table 2. Normalized Kendall tau matrix

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

Source: Table by authors

Table 3. Normalized Spearman's footrule 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

Source: Table by authors

Euzenat and Shvaiko (2007, p. 124) note that "the weighted sum can be thought of as a generalization of the Manhattan distance measure in which each dimension is weighted. It also corresponds to weighted average with normalized weights". As a result, since TOPSIS with the Manhattan distance measure can fully replicate the RCI, the result provides evidence that TOPSIS can be used as valuable alternative method to the RCI for the analysis of the competitiveness level of European territories.

When using the Euclidean distance measure, it may be noted that 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 consider pillars as being independent from each other.

As expected, the Mahalanobis ranking is the one that presents the greatest dissimilarity from the RCI, with $K^* = 0.143$ and $F^* = 0.207$, since it takes into account the correlations among the dimensions.

Figure 2 shows the closeness coefficients of the three rankings for the first 50 regions of the RCI in alphabetical order (full results are available upon request). The standard deviation of the closeness coefficients computed for the 268 regions is the lowest for the Mahalanobis ranking (0.1275), while the standard deviations of the closeness coefficients of the Manhattan and the Euclidean rankings are higher and equal to 0.1543 and 0.1416, respectively. This result is due to the adequate consideration of the correlations among the dimensions considered.

To corroborate the findings, a sensitivity analysis was carried out as shown in Figure 3, by giving the same weights to each of the 11 pillars, following scholars who have assessed the stability of TOPSIS results by using changes in weighting of the criteria (Li and Chen, 2013; Pamučar and Ranđelović, 2017). The results are robust with respect to the previous findings.

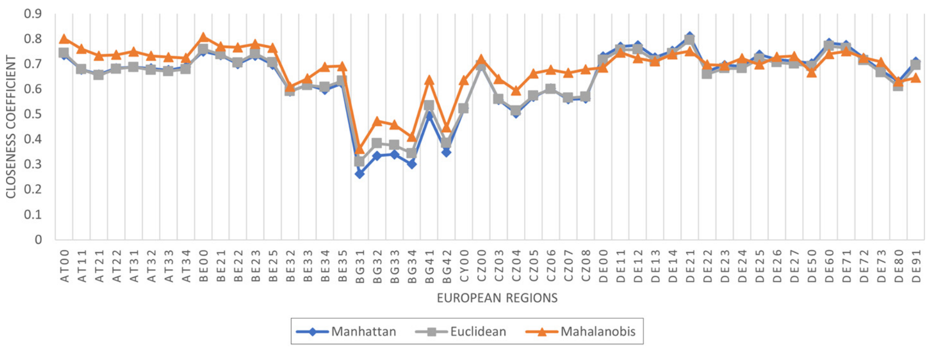

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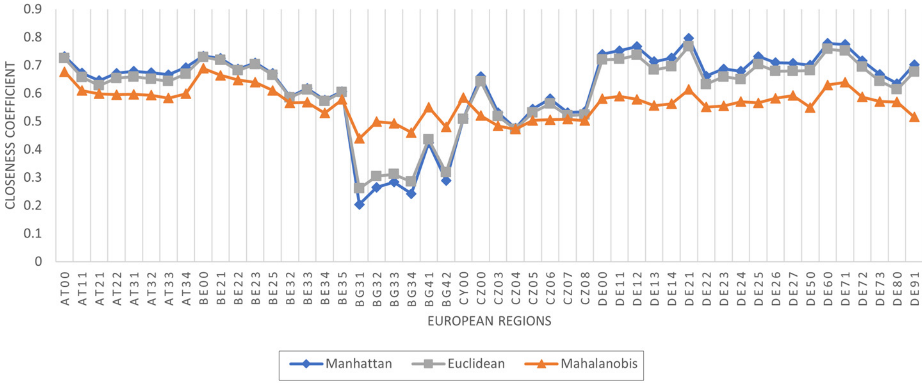
Figure 2. The closeness coefficients of the first 50 regions in the three rankings when the weights of the RCI are considered



Source: Authors's own elaboration

Figure 3. The closeness coefficients of the first 50 regions in the three rankings when equal weights are considered

While in the Manhattan and the Euclidean rankings the standard deviation of the closeness coefficient increases (0.1642 for the Manhattan and 0.1438 for the Euclidean), in the Mahalanobis ranking the standard deviation of the closeness coefficient decreases significantly to 0.0584.

As a result, the Mahalanobis ranking presents the lowest fluctuation, compared to the other two rankings, in the closeness coefficient when the weighting of the pillars is modified. This is a significant finding which corroborates the importance of considering correlations. In fact, by attributing the same weights to the pillars, the Mahalanobis distance measure is able to eliminate the overlapping information that is improperly given in the other distance measures. The main motivation for weighting indicators is to attribute more importance to certain dimensions (i.e. basic dimensions – see Figure 1) with respect to others dimension (i.e. efficiency dimensions – see Figure 1) depending on the stage of regional development (Annoni and Dijkstra, 2019). However, correlations can be intended as an additional valid point to be taken into account, accurately reflecting the characteristics of the territories analysed. The results show that, when the weights of the RCI are considered, the standard deviations of the closeness coefficients of the Mahalanobis ranking do not differ significantly from those of the two other rankings. However, when attributing the same importance to all pillars, the impact of correlation stands out as the Mahalanobis ranking has the lowest fluctuation trend, as shown in Figure 3.

In addition, in observing the regional rankings, some regions obtain a remarkably different ranking in the Mahalanobis table with respect to the ranking of the RCI and in the other two tables. For instance, Stockholm, the most competitive region in the RCI, ranks number 13 in the Mahalanobis ranking, with a remarkable drop of 12 positions. Similarly, Hovedstaden, which is ranked sixth in the RCI, falls to number 57. This can be explained by the fact that, when observing the pillars, both regions excel in the innovation dimensions such as technological readiness and innovation, which are highly weighted in the RCI as these regions are in the advanced development stage. However, they perform significantly less well on certain pillars in the basic or efficiency dimensions, such as market size, health or infrastructure which carry less weight in the overall score. Nevertheless, these indicators are closely correlated with other pillars within the same dimension, and across other dimensions (see Table 1). Consequently, the low performance of one of these basic pillars can have a significant impact on other pillars, which, in turn, affects the final ranking of the regions when correlations are considered.

At the same time, some low performing regions can significantly improve their position (i.e. West Macedonia) when considering correlations, as they stand out in some innovation dimensions which are relatively under-weighted, but which are closely and positively correlated with other basic dimensions. In short, these findings highlight that, among the distance measures adopted in this study, the Mahalanobis distance measure is the best one for the assessment of regional competitiveness.

4.2 Analysis by cluster

In the RCI, regions are clustered according to their level of competitiveness which is based on thresholds depending on the final score of the index, which depends on the score of each of the 11 pillars (see Annoni and Dijkstra, 2019 and Annoni and Kozovska, 2010 for further details). 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. To facilitate a comparison with the RCI, this section examines the changes in the composition of the clusters of the RCI when TOPSIS is applied.

Processing TOPSIS scores from highest to lowest, clusters of the same cardinality as those of the RCI were considered to facilitate the comparison. For instance, the first six regions in each ranking are placed in the first cluster, regions from positions 7 to 48 in the second one and so on, according to the cardinality of the RCI clusters. In this way, it is possible to examine changes in the composition of the clusters of the RCI when TOPSIS is applied. The division of the clusters is presented in Table 4 and follows the same division provided by the RCI. The clusters are labelled according to their stage of competitiveness. Moreover, they are ranked from the most to the least competitive, by considering the number of regions in each cluster.

It may be seen that the composition of the clusters is unaltered in the Manhattan ranking since it replicates the RCI, while in both the Euclidean and Mahalanobis rankings the composition of the clusters is altered. The modification differs depending on both the distance measure and on the typology of the cluster. Above all, it is evident that the clusters that are subject to most variation are the central ones (fairly competitive, slightly competitive, competitive, not very competitive), while extreme clusters (most competitive, highly competitive, hardly competitive, not competitive at all) are subject to less variation. To this extent, it is evident that the Mahalanobis distance measure causes major alterations to the clusters.

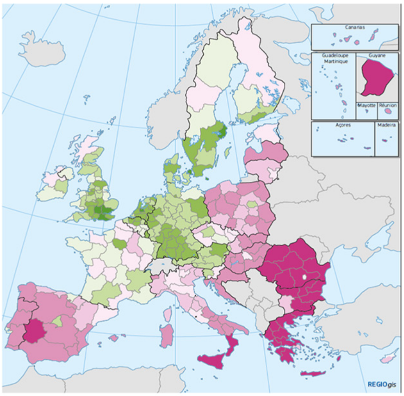
Figure 4 displays the maps of Europe according to the results of the three TOPSIS rankings and the map of the RCI. The map of the Manhattan ranking is the same as the map of the RCI, while the map of the Euclidean ranking presents some differences. While some regions improve their competitive performance such as some regions of northern Italy, and some regions in northern-eastern Greece or western Romania, 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 Swedish regions.

The map of the Mahalanobis ranking is the one that differs the most from the map of the RCI. On the one hand, a general improvement in the competitiveness level of some regions of southern countries such as central-northern Greece or some regions of Poland, Hungary or France may be observed. However, other regions are placed in a lower competitive cluster, such as some highly competitive regions of Finland and Sweden (including Stockholm, which is the most competitive region in the RCI), some middle-ranking regions of Ireland and northern Scotland, as well as eastern Germany and northern Denmark. Above all, it may

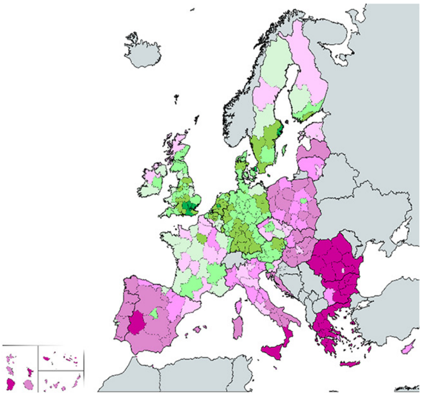
Table 4. Clusters of regions following the cardinality of the RCI and number of regions that change cluster when using TOPSIS

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%

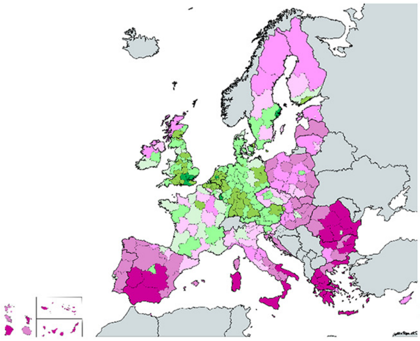
Source: Table by authors



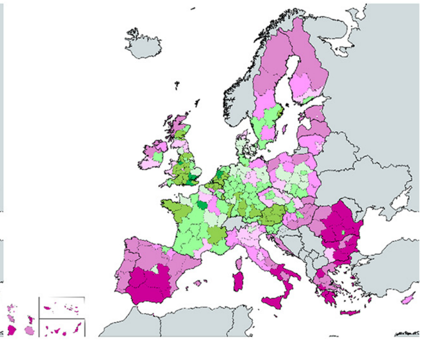
Map of the RCI (source Annoni and Dijkstra, 2019 p. 6)



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

Note: Maps at NUTS-2 level are elaborated using https://mapchart.net/
Source: Authors's own elaboration

Figure 4. European maps of the RCI and TOPSIS rankings

be observed that taking correlations into account gives rise to major differences in the composition of the clusters.

In addition, when comparing the standard deviation of the closeness coefficients in each cluster among the three rankings (Table 5), it may be seen that the Mahalanobis ranking presents the lowest standard deviation in most of the clusters considered, while the Euclidean and the Manhattan rankings present higher standard deviations. This result corroborates the findings in Section 4.1, highlighting that the Mahalanobis ranking also has the lowest fluctuation in the closeness coefficients in most of the competitiveness clusters. The Mahalanobis ranking has the highest standard deviation in the first and last clusters,

Table 5. Standard deviations of the closeness coefficients in each cluster

Ranking \ Cluster	1	2	3	4	5	6	7	8
Manhattan	0.0048	0.0287	0.0189	0.0140	0.0132	0.0207	0.0339	0.0378
Euclidean	0.0176	0.0283	0.0192	0.0105	0.0152	0.0119	0.0326	0.0424
Mahalanobis	0.0210	0.0208	0.0135	0.0062	0.0084	0.0166	0.0334	0.0685

Source: Table by authors

highlighting that those extreme clusters can be divided up further into sub-clusters for practical purposes.

From the comparative analysis of all rankings, it may be seen that some regions remain in the most performing clusters regardless of the distance measure used. These are the core leading regions in Europe (Annoni and Dijkstra, 2019; Bartkowska and Riedl, 2012; Iammarino and Rodríguez-Pose, 2017), such as Inner London or Surrey and some highly competitive regions of The Netherlands or Belgium. At the same time, it may be seen that there are several peripheral regions of southern and eastern Europe (e.g. regions of southern Italy, as well as regions of southern Greece and eastern Romania) that, despite the distance metric used, are always placed in the lowest performing cluster. Hence, this result highlights their stagnation in regional development (Iammarino and Rodríguez-Pose, 2017), which might be exacerbated by their geographical location that excludes these regions from spillover effects of more advanced regions (Annoni and Dijkstra, 2019).

Generally, the regional competitiveness in Europe still exhibits great differences and disparities (Borsekova *et al.*, 2021b; Dagilienė *et al.*, 2020; Moirangthem and Nag, 2022). The findings of this comparative analysis are in line with evidence provided by other authors (e.g. Annoni *et al.*, 2016; Camagni and Capello, 2013; Möbius and Althammer, 2020), who showed that regional convergence in Europe is far from being fully achieved.

5. Concluding remarks, limitations and future research

Various authors have argued in favour of further investigating the measurement of regional competitiveness, as regions are major levers for the development of a country. In this regard, researchers suggest considering the issue of correlation since competitiveness dimensions are usually interrelated (Pontarollo and Serpieri, 2021). In this sense, cumulative causation theory underlines how economic growth is driven by interrelated factors as changes in one macroeconomic dimension affect changes in others (Lehtonen and Tykkyläinen, 2018). Some scholars indicate MCDM methods as a valuable alternative to composite indices in this regard, which can also deal with the aspect of correlation. By addressing three different research questions, this study recalculates the RCI 2019 by means of TOPSIS based on the Manhattan, Euclidean and Mahalanobis distance measures, and considers in the analysis rankings and cluster of competitiveness, taking the RCI as a frame of reference.

The findings are important in two respects. The first point to consider is that regarding the method used, the application of TOPSIS was extended to regional competitiveness at the European level, which has attracted limited attention so far, arguing in favour of TOPSIS as a valuable alternative method in the assessment of regional competitiveness with respect to the others in the literature (Borsekova *et al.*, 2021a; Bronisz *et al.*, 2008). In particular, as the RCI can be obtained as a result of a

TOPSIS application with a less preferred choice of distance measure (Manhattan), constitutes a strong point in favour of TOPSIS in the analysis of regional competitiveness, as the study provides the same results as the European Union with a different calculation method. In addition, consistent with cumulative causation theory, the findings highlight the importance of considering correlation, as neglecting them can distort the analysis, which is a common issue in composite indicators (Wang and Wang, 2014). In fact, as the Mahalanobis distance measure deals with this aspect, this constitutes an additional point in favour of the application of TOPSIS by policymakers for the purposes of regional analysis. In particular, the Mahanalobis ranking was found to be the most robust among the three rankings obtained, as it shows the lowest fluctuation in the closeness coefficient, even when robustness checks are applied. This finding emphasizes the importance of considering correlation in the measurement of regional competitiveness, as it accounts for the interdependencies across the various dimensions. Hence, this result enriches the theoretical discussion about cumulative causation and the importance of self-reinforcing cumulative circles of macro-economic dimensions, with a significant impact on the measurement of regional development.

At the same time, the result contributes to policymaking discussions, as considering or failing to consider the aspect of correlation can lead to different results and decisions. There is good reason for policymakers to use TOPSIS with the Mahalanobis distance measure when analysing the competitiveness level of regions, as it is a valid alternative for dealing with certain critical aspects in the use of composite indices, providing a more accurate measurement of regional development (Arcagni *et al.*, 2021; Bristow, 2010).

The second point to consider is that the comparison between the rankings and between the cluster of competitiveness obtained casts light on the persistent differences and disparities in regional development within the European Union (Borsekova *et al.*, 2021b; Dagilienė *et al.*, 2020; Moirangthem and Nag, 2022). In particular, the results provide further evidence of a small number of leading regions that can be considered as the economic backbone of European prosperity, while others present persistent weaknesses. This finding aligns with and confirms prior findings that highlight how the process of regional development is still far from being fully accomplished (Beltran *et al.*, 2024; Borsekova *et al.*, 2021b). At the same time, the findings should be an alert for public institutions dealing with regional development, because, while some leading regions are always placed in the most performing cluster, others some less competitive are consistently placed into the lowest performing cluster, regardless the distance measure used. As a result, as argued in the literature (Pinheiro *et al.*, 2022), this pattern can create problems regarding the effective implementation of regional development policies because less developed regions benefit less than more developed ones and the persistent difference in regional development can give rise to geographical inequality loops. The findings of this study emphasize the importance of considering clusters in the analysis of regional development, to obtain a more comprehensive measurement and richer insights.

The present analysis considers cross-section data, which provide only a snapshot of the regional competitive situation in Europe. However, when investigating regional competitiveness or territorial disparities, most researchers rely on time-series data (Bartkowska and Riedl, 2012; Bosker, 2009). As a result, as a further step of this analysis, it would be useful to replicate it at different points in time, by examining the RCI from 2010 to 2019 to investigate how the rankings of regions and the composition of clusters change over time.

Notes

1. see https://ec.europa.eu/regional_policy/information-sources/publications/working-papers/2019/the-european-regional-competitiveness-index-2019_en for further details
2. In this study, a different weighting scheme is not used as the intention is to replicate the RCI. See Section 4 for a robustness check of the results with an equal weighting scheme.

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Appendix

Table A1. Position of the first 50 European regions in the different rankings (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 and other	2	2	1	Oost-Vlaanderen	31	24	17
Utrecht	3	4	3	Berlin and other	32	34	114
Berkshire and other	4	3	18	Overijssel	33	48	40
Surrey and other	5	1	2	Östra Mellansverige	34	78	100
Hovedstaden	6	12	57	Västsverige	35	76	103
Luxembourg	7	6	9	Herefordshire and other	36	32	39
Oberbayern	8	8	32	North Yorkshire	37	29	12
Flevoland and 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 and other	41	31	21
Darmstadt	13	14	33	Düsseldorf	42	45	70
Zuid-Holland	14	18	14	Gr Manchst.	43	30	16
Hampshire and 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 and other	22	15	10				
Tübingen	23	23	43				
Sydsverige	24	50	62				
Bruxelles and other	25	16	7				
Kent	26	26	38				
Limburg	27	35	35				
Mittelfranken	28	33	97				
Wien and other	29	22	8				

Source: Table by authors