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# A poset-based analysis of regional innovation at European level

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## Abstract

This paper examines the performance of regional innovation across 220 European regions. First, a cluster analysis is performed in order to detect patterns of comparable regions. Subsequently, a poset-based approach is adopted to obtain a ranking of the different clusters of European regions. The outcome is compared with the results described in the Regional Innovation Scoreboard 2019. Useful insights for policymakers are obtained.

## Keywords

Regional innovation, partially ordered set, poset, Regional Innovation Scoreboard, European Union

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## Abstract

This paper examines the performance of regional innovation across 220 European regions. First, a cluster analysis is performed in order to detect patterns of comparable regions. Subsequently, a poset-based approach is adopted to obtain a ranking of the different clusters of European regions. The outcome is compared with the results described in the Regional Innovation Scoreboard 2019. Useful insights for policymakers are obtained.



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## 1. Introduction

Innovation is a key driver of economic growth [1, 2], which is widely considered as conducive to improvements in standards of living [3]. Over the last decades, several innovation systems have been developed, at the national [4] as well as regional level [5]. Such systems are thought to be the most reliable representation of the environment that is needed to create and develop innovation [6]. However, most policymakers and researchers agree that innovation is primarily determined at the regional level [7, 8, 9]. In fact, although the free movement of capital and labour is increasing, knowledge accumulation and exploitation remain spatially concentrated [10, 11, 12], and highly subordinated to socioeconomic and institutional conditions [13] as well as the capacity of a region to generate knowledge spillovers [14].

In the literature, the Regional System of Innovation (RSI), or Regional Innovation System (RIS) concept has been widely studied. It consists of actors, such as organisations, institutions, firms and stakeholders, and of the relationships between them [15, 16, 17, 18]. These linkages should be encouraged and supported to generate positive results [19], as good regional innovation patterns positively influence regional economic performance [20]. It is essential for policymakers to evaluate these patterns in a proper manner in order to better use the available resources to improve the results.

Measuring innovation at the regional level involves the choice of indicators. Some of the indicators that are considered to measure regional innovation performance are related to investment in research and development activities at both the public and private level, the support for public-private partnerships and the number of researchers employed in the region [21]. In particular, technology development efficiency is higher in regions where R&D is more public-focues [22]. Moreover, knowledge creation, absorptive capacity and governance capacity are found to play a role in innovation [8, 23]. The number of patents per capita is also a main driver of innovation [24] in cases in which the restrictions on intellectual property are not too strict [25]. Other studies find that it is important to monitor the innovation activities through indicators such as the percentage of SMEs that are innovating in-house for firms in high-concentration markets [26, 27], or the number of collaborations among innovative SMEs aiming to enhance new-to-the-firm forms of innovation [28]. Also the sales of new-to-market and new-to-firm innovations as a percentage of total turnover should be considered to evaluate the sales impact [29]. These indicators are included in the most exhaustive available index that makes a comparative assessment of the innovation performance at the regional level: the Regional Innovation Scoreboard (RIS). It considers indicators subdivided into four pillars: framework conditions, investments, innovation activities and impacts [30, 31].

From a classical point of view, as conceptualised by Schumpeter - one of the most influential economists of the twentieth century - innovation systems are complex systems [32]. The same concept has been adopted more recently by other authors [33, 34]. An appropriate method is required to analyse such systems in the best possible way and better orient public policies for creating regional advantages in different contexts [35]. The method considered as reference point in the analysis of such complex systems is the Regional Innovation Scoreboard, that provides a final ranking of the European regions based on the average value of the indicators considered, making it more difficult to clearly detect whether a region is underperforming on some of the indicators.

In this paper, we adopt an approach borrowed from the theory of partially ordered sets (theory of posets, or poset theory, for short; see Subsection 3.2), that will allow us to capture and represent the complexity of the measurement of regional innovation performance. The poset-based approach can be seen as an alternative to the use of composite indicators. It has been adopted for different purposes, including the calculation of new indices on the stringency of fiscal rules [36], the evaluation of multidimensional poverty [37], the assessment of river water quality [38], the synthetisation of multi-indicator systems over time [39], and various applications in chemistry [40]. The main strengths of the poset-based approach can be summarised as follows: it respects the ordinal nature of data, it maintains a high standard of objectivity (hence, reducing the need for subjective choices), and it fully exploits all information contained in the dataset [36]. Through these characteristics, it is possible to identify relevant insights such as the impact of indicators in the construction of the ranking. We apply the poset-based approach to the regional data available from the RIS 2019 (the most recent ranking). The analysis consists of two steps: first, a clustering of the regions is carried out, and second, the poset-based approach is applied to establish a ranking of these clusters. The application of the poset-based approach is feasible even on a large dataset with thousands of observations, thanks to the cluster analysis and the attribute-related sensitivity analysis proposed in this paper.

This paper is organised as follows. Section 2 analyses the methods applied to measure regional innovation performance and describes the Regional Innovation Scoreboard 2019. Section 3 presents the dataset and the methods used, with particular attention to the description of the poset theory and the various steps of the analysis. Section 4 presents the results of the study. The last section is dedicated to the discussion of findings, conclusions, limitations, and perspectives for future research. Appendix A shows an example of data analysis using the poset-based approach illustrating the steps performed in this work. Appendix B describes the regions analysed in the study and provides additional information about the clusters and the membership to a performance group.[1] We observe certain differences in the performance group membership for some European regions compared to the results of the Regional Innovation Scoreboard 2019. This comparison could be of interest to policymakers and innovation

[1] In Appendix B, all 220 European regions analysed in this study are listed following the order of the ranking obtained after the data analysis from the poset-based approach, comparing their performance group both in the poset-based analysis and in the RIS 2019.

ecosystem actors to gain a better understanding of which regions are similar in terms of innovation performance and which indicators should be targeted in order to increase the position of a cluster of regions in the ranking.

## 2. How regional innovation is measured

Since the beginning of the 1990s, studies about innovation have been on the rise, due to the need to understand the driving forces leading to a high innovation performance and the best methods to describe the phenomenon of innovation. In Subsection 2.1 we review the currently available indices and in Subsection 2.2 we describe the Regional Innovation Scoreboard, which is taken as our benchmark.

### *2.1 Currently available indices*

Measuring the innovation performance of a region is a difficult task, due to the changing nature of innovation, in particular since the development of the global economy [41]. Furthermore, even if finding data at regional level is harder than at national level, regional data availability is better than before, allowing for a more sophisticated assessment of innovation performance [42]. Before considering the most effective way to measure regional innovation performance, it may be useful to provide a literature review of the state-of-the-art on the measurement of innovation performance in a broader context.

One of the most popular methods for measuring innovation is to consider a single indicator, such as patent statistics [43, 44]; this method is frequently used to measure innovation at the firm level [45], [46]. Another approach frequently adopted is the use of an extensive set of indicators [30, 47], which makes it possibile to construct different typologies of innovation processes. A third method considers a number of innovation indicators to create a composite index. This holds, for instance, for the Bloomberg Innovation Index, the Global Innovation Index and the European Innovation Scoreboard, the most frequently adopted indices to cast light on innovation and compare performances at the country level [48]. Starting from the European Innovation Scoreboard, the Regional Innovation Scoreboard has been developed, collecting data about all the regions of the European Union and the neighboring regions.

The discussion about which approach should be considered the best for the measurement of innovation performance is still open. However, for each of the three methods discussed above, some problems have been identified. For instance, the adoption of a single indicator is useful only in cases in which the focus of the analysis is on a specific aspect of innovation: to find more evidence of the innovation performance of a region, multiple indicators are required [30]. Moreover, as suggested by some researchers, policymakers should contemplate the results of different analyses to obtain a more comprehensive view of a regional innovation system [49], as innovation is a complex phenomenon that cannot be entirely explained with the use of proxy statistics; as a result, linkages between input indicators and output (intended to describe innovation performance) could be fuzzy.

Despite the existence of various composite indicators to measure innovation, as discussed above, the most popular is the European Innovation Scoreboard (EIS), as it provides a comparative assessment of all European Member States, facilitating the understanding of which areas they should focus on in order to improve their results [31, 50]. The Regional Innovation Scoreboard (RIS) has been developed on the basis of the EIS and is considered the most important index at the regional level [30]. It assesses the innovation performance of European regions since 2009 and at present covers more than two hundred regions. For this reason, the RIS dataset is at the basis of this study and will be extensively discussed in the next section. Similar to the work of researchers in other fields [51], our poset-based approach aims to provide more insight into the complex phenomenon of regional innovation by relying on ordinal data, avoiding the use of more synthetic measures such as ranks constructed simply on the basis of the average of indicators.

### *2.2 Regional Innovation Scoreboard*

The Regional Innovation Scoreboard (RIS) is the regional extension of the European Innovation Scoreboard (EIS). The most recent EIS ranking, published in 2019, assesses the innovation performance of all 27 member states of the EU, in addition to other non-EU countries (including the United Kingdom), analysing the scores of 27 different indicators. As already mentioned, the regional availability of the data is more complex, in fact, the RIS 2019 is limited to the use of regional data for 17 of the 27 indicators included in the EIS. The RIS 2019 is the ninth annual ranking, and the regional coverage has increased compared to previous years. It now includes 238 NUTS 2 (Nomenclature of Territorial Units for Statistics) representing 22 European countries, including Norway, Serbia, Switzerland and the United Kingdom. It also includes five NUTS 1 (countries: Cyprus, Estonia, Latvia, Luxembourg, and Malta) that are considered in the same way as NUTS 2. Hence, the total number of objects (regions and countries) analysed is 243.

The 17 indicators are grouped into four different categories: framework conditions (population aged 30-34 with tertiary education, lifelong learning, international scientific co-publications, top 10% most cited publications), investments (R&D expenditure in public sector, R&D expenditures in business sector, non-R&D innovation expenditure), innovation activities (SMEs with product or process innovations, SMEs with marketing or organisational innovations, SMEs innovating in-house, innovative SMEs collaborating with others, public-private co-publications, PCT patent applications, trademark applications, design applications), and impacts (knowledge-intensive services exports, sales of new-to-market and new-to-firm innovations).

The regional data of the listed indicators are taken mostly from Eurostat; other sources include the OECD REGPAT database, Community Innovation Survey (CIS) data, National Statistical Offices, CWTS (Leiden University) as part of a contract with the European Commission (DG Research and Innovation). Before imputation, data availability is 90.9%, even if 10 out of 17 indicators have an availability of at least 95%. After the application of several imputation techniques (based on the availability of regional or national data referring to the previous year of observation), data availability increases to 98.9% and some data are still missing just for a few regions of 10 different countries, with Ireland and Serbia showing the lowest result: 94.1%. Data is then normalised adopting the min-max procedure. The minimum and the maximum are calculated based on the data of the last five biennial observations. The final index is obtained by applying a country correction factor (based on the results at the national level reported in the EIS) to the average of the normalised scores of the 17 indicators [52].

Once the scores have been calculated, the regions are grouped into four different categories: innovation leaders with a relative performance higher than 120% of the EU average; strong innovators with a relative performance between 90% and 120% of the EU average; moderate innovators with a relative performance between 50% and 90% of the EU average; and modest innovators with a relative performance below 50% of the EU average. The RIS 2019 includes 38 regions in the group of innovation leaders, 170 in the middle groups (73 regions as strong innovators and 97 as moderate innovators) and 30 in the group of modest innovators. Each performance group is further divided into three subgroups. Regarding the performance, the leaders are mostly regions from Switzerland, Finland, Sweden, the United Kingdom, Denmark, the Netherlands, and Germany, whereas the modest innovators are mostly regions from Poland, Bulgaria, and Romania [31].

An interesting aspect of the RIS 2019 is the average score of the indicators per regional performance group. Considering the EU average equal to 100, the report of the RIS 2019 shows that 15 out of 17 indicators have the best score in the leaders group and the worst score in the modest group. Just two indicators follow a different pattern. The first one is the indicator *innovative SMEs collaborating with others,* which has a slightly higher score in the strong innovators group than in the leader innovator group (126 vs 118); however, the difference is small, and in the moderate and modest innovator groups the score is much lower compared to the leader innovator group. The second one is the indicator *non-R&D innovation expenditures*, which shows the highest scores in the strong and moderate innovator groups, whereas in the innovation leaders group, it has an outcome similar to that of the modest innovator group. Hence, it seems that in this context, this indicator does not respect the outcomes of the innovation performance groups. The problems with the *non-R&D innovation expenditures* indicator have been discussed before in the literature, for instance, in [53] and [54]. For this reason, it was decided to exclude this indicator from our analysis.

A limitation of the Regional Innovation Index lies in the fact that the final regional score is simply computed as the average of all indicators, which could be affected by so-called compensation effects, as in the case of arithmetic addition [55, 56]. To be more precise, the low performance of a region for one indicator could be compensated by a high score for another one. Limitations of the RIS have been also identified in [57], where the ranking was revisited by using a multiple criteria decision analysis approach combining AHP and TOPSIS methods in the context of the Quadruple Innovation Helix framework. In this paper, we propose to use a poset-based approach that, unlike [57], permits to identify the indicators with the strongest impact, which are used to construct a ranking of the clusters.

## 3. Material and methods

In this section, we provide a description of the dataset adopted for the study of regional innovation (Subsection 3.1) and of the methods adopted in the different steps of our investigation (Subsection 3.2).

### *3.1 Material*

The analysis has been performed on the dataset obtained from the website of the Regional Innovation Scoreboard 2019.[2] As explained in Section 2, we exclude the indicator *non-R&D innovation expenditures* from the dataset. The full dataset therefore contains data for the 16 indicators discussed in Section 2. In our analysis we considered 220 regions out of 238: the 208 regions of the EU Member States (involving in total 22 different countries), plus the 12 regions of the United Kingdom that were part of the EU in 2019. We excluded the non-EU regions (Norway, Switzerland, and the Republic of Serbia).[3] All regions are NUTS 2.

### *3.2 Methods*

The initial data matrix is composed of 220 objects (regions) and 16 indicators (attributes), with 31 missing data. The first step of the analysis is the imputation of the missing data. To this end, we used the nearest neighbour imputation method, a commonly applied method [58]. More precisely, we considered the five nearest neighbour values for computing each of the missing data. The imputation was done for each indicator separately. After imputation, the data matrix contains 3520 observations.

The application of the poset-based approach to a large dataset could generate results that are difficult to interpret. As a result, we reduced the number of objects (regions) through a cluster analysis by

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[2] The database is available at the following link: https://bit.ly/3cc8PAP.

[3] We did not consider small European countries such as Cyprus, Estonia, Latvia, Luxembourg and Malta in the analysis. In the RIS 2019, their data at country level was used in the NUTS 2 analysis.

performing a hierarchical clustering with the default distance measure, namely the Euclidian distance measure; the function used is 'hclust' with the complete linkage method (using the software R). The scores of the clusters correspond (for each attribute) to the average of the scores of the objects that compose each cluster. The number of attributes (indicators) is reduced to two through the attribute-related sensitivity method (see Appendix A, Table A.4). After the reduction of both the number of objects and attributes, the last step corresponds to the application of the poset-based approach to the final data matrix (composed of the 11 clusters of regions and the two most impacting indicators for each of the four categories) to create a ranking (using the software PyHasse).

The main assumption of the poset-based approach is summarised as follows. Two objects (a and b) that are compared on the basis of two different attributes ($q_1$ and $q_2$) can be ordered (ranked) if and only if one of them has at least the same performance as the other one on both attributes (in the unlikely case of exactly the same performance, the objects would be tied). On the contrary, if, for instance, a has a higher performance than b on $q_1$ and b has a higher performance than a on $q_2$, then the two objects are called incomparable, and it is not possible to establish an order between them [59].

The ordering of the objects can be represented graphically through a Hasse diagram, which makes it possible to visually display the most important characteristics of a partially ordered set (poset, for short): the relationships among objects, and the isolated elements (objects that are not comparable with any other object). To better understand the characteristics of this approach, we provide an example in Appendix A.

## 4. Results

As explained in the previous section, after the imputation of the missing data, the dataset is composed of 220 regions belonging to 22 countries of the European Union plus the United Kingdom and includes 16 indicators. As 3520 data are too many to be analysed with the poset-based approach, it is necessary to create clusters of regions.

### *4.1 Cluster analysis*

The first step is the computation of the distance matrix, showing for each pair of objects (regions) their Euclidean distance considering all the indicators. The clusters are then created based on the distance matrix according to the complete linkage method.

The choice of the number of clusters ($k$) is based on the inspection of the scree plot. One of the most popular methods for selecting the number of clusters is the 'elbow method' [60]; however, as no elbow is visible in the scree plot in our case, we decided to select a number of clusters to be able to reduce the 'within group sum of squares' and at the same time obtain a sufficiently rich partial order. This is attained by choosing a number of clusters ranging from 8 to 11. We chose the maximum number of clusters (11) to limit the variability inside clusters. In this case, the matrix is formed by 11 rows (clusters of regions) and 16 columns (indicators). The elements of the matrix represent the average value of the regions that are included in the cluster, for each indicator.[4] We also report the results considering eight clusters to validate the results obtained with 11 clusters.

According to the cluster analysis performed, the number of regions included in the different clusters is not homogeneous. In particular, we observe a large cluster consisting of 61 regions (cluster n°2) and another one that includes just one region (cluster n°11).[5] This is the first result of the analysis: the Finnish region of Åland (an archipelago) shows data that is incomparable with all other regions included in the dataset, and, with $k = 11$, it is impossible to include it in any cluster.

*4.2 Attribute-related sensitivity analysis*

In order to reduce the number of indicators from 16 to 8, in this step of the analysis we aim to select the two most impacting indicators for each of the four categories. Since the two categories *investments* and *impacts* are formed by two indicators each, it is not necessary to perform any reduction for them. As a result, we apply the attribute-related sensitivity analysis to the two remaining categories. We reduce the four indicators of the category *framework conditions* and the eight indicators of the category *innovation activities*.

Starting with *framework conditions*, we consider a data matrix consisting of the 11 clusters as objects and the four indicators of the category under analysis. After obtaining the Hasse diagram representing the relationships among the clusters for this category, it is important to compute the total number of incomparabilities as an estimate of the complexity of the poset, and then to find the pair of indicators that reproduces the closest number of incomparabilities. There are 24 incomparabilities in the Hasse diagram generated considering all four attributes of the category. The indicators *population aged 30-34 with tertiary education* and *lifelong learning* alone create 17 incomparabilities (71% of the total); thus, they are the ones with the strongest impact for the category and will be considered in the final data matrix.

Regarding the category *innovation activities*, there are eight indicators. As a result, the number of possible pairwise combinations is quite high. In this case, the pair of indicators with the strongest impact

[4] The score of a cluster is the averages of the scores, between 0 and 1 (normalised values), of the regions that compose the cluster.

[5] As some clusters contain several regions, the variability inside these clusters could be quite high. As a result, some regions might be considered as outliers of such cluster (as in the case of Drenthe and Valle d'Aosta).

is formed by *innovative SMEs collaborating with others* and *design applications*, representing 31 incomparabilities out of a total of 36 (86%).

At this stage, we are able to construct the final data matrix that is shown in Table 1: 11 clusters and eight indicators, representing the two with the strongest impact for each category, listed as follows. 1. Framework conditions: 1a. *Percentage of population aged 30-34 having completed tertiary education*; 1b. *Lifelong learning, the share of population aged 25-64 enrolled in education or training aimed at improving knowledge, skills, and competences*. 2. Investments: 2a. *R&D expenditure in public sector as percentage of GDP*; 2b. *R&D expenditure in business sector as percentage of GDP*. 3. Innovation activities: 3a. *Innovative SMEs collaborating with others as percentage of SMEs*; 3b. *Individual design applications per billion GDP (in purchasing power standards)*. 4. Impacts: 4a. *Employment in medium-high and high-tech manufacturing and knowledge-intensive services*; 4b. *SMEs sales of new-to-market and new-to-firm innovations as percentage of total turnover*.

*Table 1 – Final data matrix: 11 clusters and 8 indicators with the strongest impact (data normalised)*

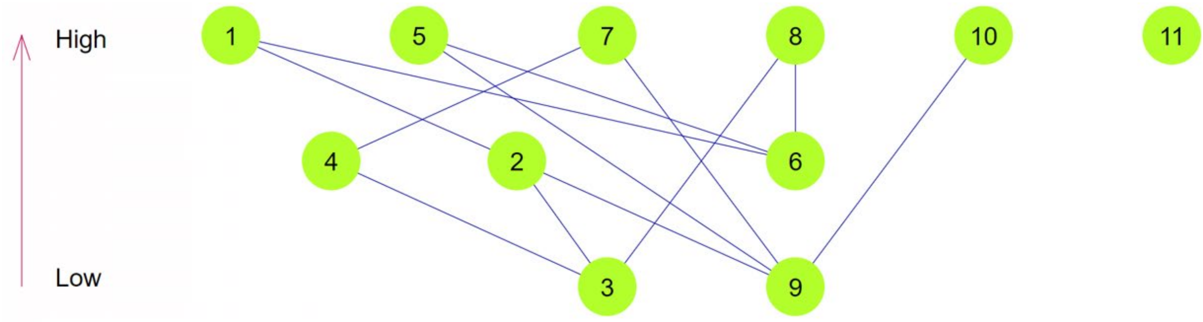
| ***Cluster*** | ***1a*** | ***1b*** | ***2a*** | ***2b*** | ***3a*** | ***3b*** | ***4a*** | ***4b*** |
|---|---|---|---|---|---|---|---|---|
| **1** | 0.560 | 0.551 | 0.605 | 0.704 | 0.592 | 0.458 | 0.511 | 0.563 |
| **2** | 0.329 | 0.329 | 0.467 | 0.476 | 0.352 | 0.455 | 0.476 | 0.545 |
| **3** | 0.289 | 0.054 | 0.199 | 0.212 | 0.090 | 0.399 | 0.293 | 0.284 |
| **4** | 0.526 | 0.151 | 0.379 | 0.392 | 0.164 | 0.517 | 0.409 | 0.369 |
| **5** | 0.731 | 0.284 | 0.514 | 0.526 | 0.339 | 0.344 | 0.691 | 0.530 |
| **6** | 0.355 | 0.210 | 0.265 | 0.317 | 0.208 | 0.231 | 0.394 | 0.503 |
| **7** | 0.725 | 0.898 | 0.824 | 0.745 | 0.506 | 0.597 | 0.688 | 0.500 |
| **8** | 0.398 | 0.266 | 0.772 | 0.663 | 0.276 | 0.605 | 0.683 | 0.531 |
| **9** | 0.282 | 0.145 | 0.181 | 0.445 | 0.313 | 0.163 | 0.236 | 0.497 |
| **10** | 0.541 | 0.276 | 0.352 | 0.510 | 0.918 | 0.306 | 0.360 | 0.877 |
| **11** | 0.293 | 0.724 | 0.251 | 0.078 | 0.838 | 0.146 | 0.436 | 0.110 |

The entries for cluster n°11 are just those of Åland since it is the only region in this cluster.

### *4.3 Poset-based analysis*

The Hasse diagram obtained from the final data matrix is shown in Figure 1.

*Figure 1 – 11 clusters (220 European regions), Hasse Diagram*




The Hasse diagram clearly shows the relations between the clusters. For instance, it is evident that clusters 1, 5, 7, 8 and 10 do not have any links with clusters positioned at a higher level. At the same time, clusters 3, 6 and 9 do not have any links with clusters positioned at a lower level. Cluster 11 deserves special attention as it is the only one that is incomparable with all the other clusters. We already expected this result as cluster 11 consists of just one region, which is the Finnish archipelago of Åland; hence, as already commented, the scores for cluster 11 coincide with the data of Åland itself. To obtain and discuss the ranking of the clusters, we should look at the final score of each cluster, which is obtained by applying the Local Partial Order Model (LPOM).

The Local Partial Order Model highlights three levels of performance: the top level composed of, in order, clusters 1, 7, 5 and 8 (the last two have the same score); the middle level, formed by clusters 10, 2, 11 and 4; finally, the low level, containing clusters 6, 9 and 3.

The regions in the top and the bottom level are quite equally distributed (64 vs 67 regions), while the middle level is the one with the highest number of regions: 89. At this level, we find both cluster 2, consisting of 61 regions, and cluster 11, the one-of-a-kind cluster (Åland). Åland is incomparable with all the other clusters since it has a very good performance on some indicators such as *lifelong learning* and *innovative SMEs collaborating with others*, whereas it has a very low performance on other indicators, including *R&D expenditure in business sector*, *design applications* and *sales of new-to-market and new-to-firm innovations*. More detailed results are provided in Figure 2, which shows the composition of each cluster and gives information about the number of regions for each country.

*Figure 2 – Composition of the 11 clusters (220 European regions)*

| Cluster | BE | BG | CZ | DK | DE | IE | EL | ES | FR | HR | IT | LT | HU | NL | AT | PL | PT | RO | SI | SK | FI | SE | UK | TOTAL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2 | | | 2 | 3 | | | | 4 | | | | | 7 | 3 | | | | | | 3 | 2 | 3 | **29** |
| **7** | | | | 2 | | | | | | | | | | | | | | | | | 1 | 3 | | **6** |
| **8** | | | | | 17 | | | | | | | | | 1 | | | | | | | | | | **18** |
| **5** | | | 1 | | | 2 | | 4 | | | | | 1 | | | 1 | | | 1 | 1 | | | | **11** |
| **10** | | | | | | | 5 | | | | | 1 | | | | | | | | | | | 8 | **14** |
| **2** | 1 | | 6 | 1 | 18 | 1 | 1 | | 8 | | 12 | | 1 | 3 | | | 4 | | 1 | | | 3 | 1 | **61** |
| **11** | | | | | | | | | | | | | | | | | | | | | 1 | | | **1** |
| **4** | | 1 | | | | | | 4 | | | | | | | | 7 | | 1 | | | | | | **13** |
| **6** | | | 1 | | | | | 10 | | 1 | 1 | | 6 | 1 | | | | | | 3 | | | | **23** |
| **9** | | | | | | | 7 | | 2 | 1 | 8 | 1 | | | | | 3 | | | | | | | **22** |
| **3** | | 5 | | | | | | 1 | | | | | | | | 9 | | 7 | | | | | | **22** |
| **TOTAL** | **3** | **6** | **8** | **5** | **38** | **3** | **13** | **19** | **14** | **2** | **21** | **2** | **8** | **12** | **3** | **17** | **7** | **8** | **2** | **4** | **5** | **8** | **12** | **220** |

| | BE | BG | CZ | DK | DE | IE | EL | ES | FR | HR | IT | LT | HU | NL | AT | PL | PT | RO | SI | SK | FI | SE | UK | TOTAL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Level 1** | 2 | 0 | 1 | 4 | 20 | 2 | 0 | 4 | 4 | 0 | 0 | 0 | 1 | 8 | 3 | 1 | 0 | 0 | 1 | 1 | 4 | 5 | 3 | **64** |
| **Level 2** | 1 | 1 | 6 | 1 | 18 | 1 | 6 | 4 | 8 | 0 | 12 | 1 | 1 | 3 | 0 | 7 | 4 | 1 | 1 | 0 | 1 | 3 | 9 | **89** |
| **Level 3** | 0 | 5 | 1 | 0 | 0 | 0 | 7 | 11 | 2 | 2 | 9 | 1 | 6 | 1 | 0 | 9 | 3 | 7 | 0 | 3 | 0 | 0 | 0 | **67** |

The clusters are ordered from top-performing to low-performing. It should be noted that clusters 5 and 8 are tied in the ranking. As regards the colours, blue represents the top-performing clusters, green identifies the middle-performing ones, and red the low-performing clusters. Looking at column DE, for instance, we can see that Germany has 20 regions in the top level clusters (three regions in cluster 1, which is the first in the ranking, and 17 regions in cluster 8) and 18 regions in cluster 2, which belongs to the middle level. To provide another example of how to read Figure 2, it may be said that cluster 1 is composed of regions from Austria, Belgium, Denmark, Finland, France, Germany, the Netherlands, Sweden, and the United Kingdom, while cluster 3 (the last in the ranking) contains regions from Bulgaria, Poland, Romania, and Spain.

The second part of Figure 2 shows that the only country that has all regions in top-performing clusters is Austria. Moreover, Belgium, Denmark, Finland, Germany, Ireland, the Netherlands, and Sweden have the majority of regions in top-level clusters; on the other hand, more than half of their regions of Bulgaria, Croatia, Greece, Hungary, Poland, Romania, Slovakia and Spain are in low-level clusters. The complete list of all regions and their respective cluster and level of performance is available in Appendix B. For each region it is possible to identify the other regions that are grouped in the same cluster as well as the position of the cluster in the ranking.

### *4.4 Robustness*

To validate the ranking obtained with 11 clusters, we now repeat the analysis considering just eight clusters, which represents the minimum number of clusters that makes it possible to reduce the 'within group sum of squares' and at the same time avoids the generation of many incomparable clusters in the Hasse diagram. In this case, the final data matrix is of size 8x8 and the most impacting indicators obtained from the attribute-related sensitivity analysis are the same eight indicators obtained in the study with 11 clusters except one: *lifelong learning* is substituted by *scientific publications among the top-10% most cited publications worldwide as percentage of total scientific publications of the country*.

Regarding the new composition of the groups of regions, clusters 7 and 1 of the analysis based on 11 clusters are now joined together into a single cluster. This is also the case for clusters 6 and 4, and for clusters 11 and 9.

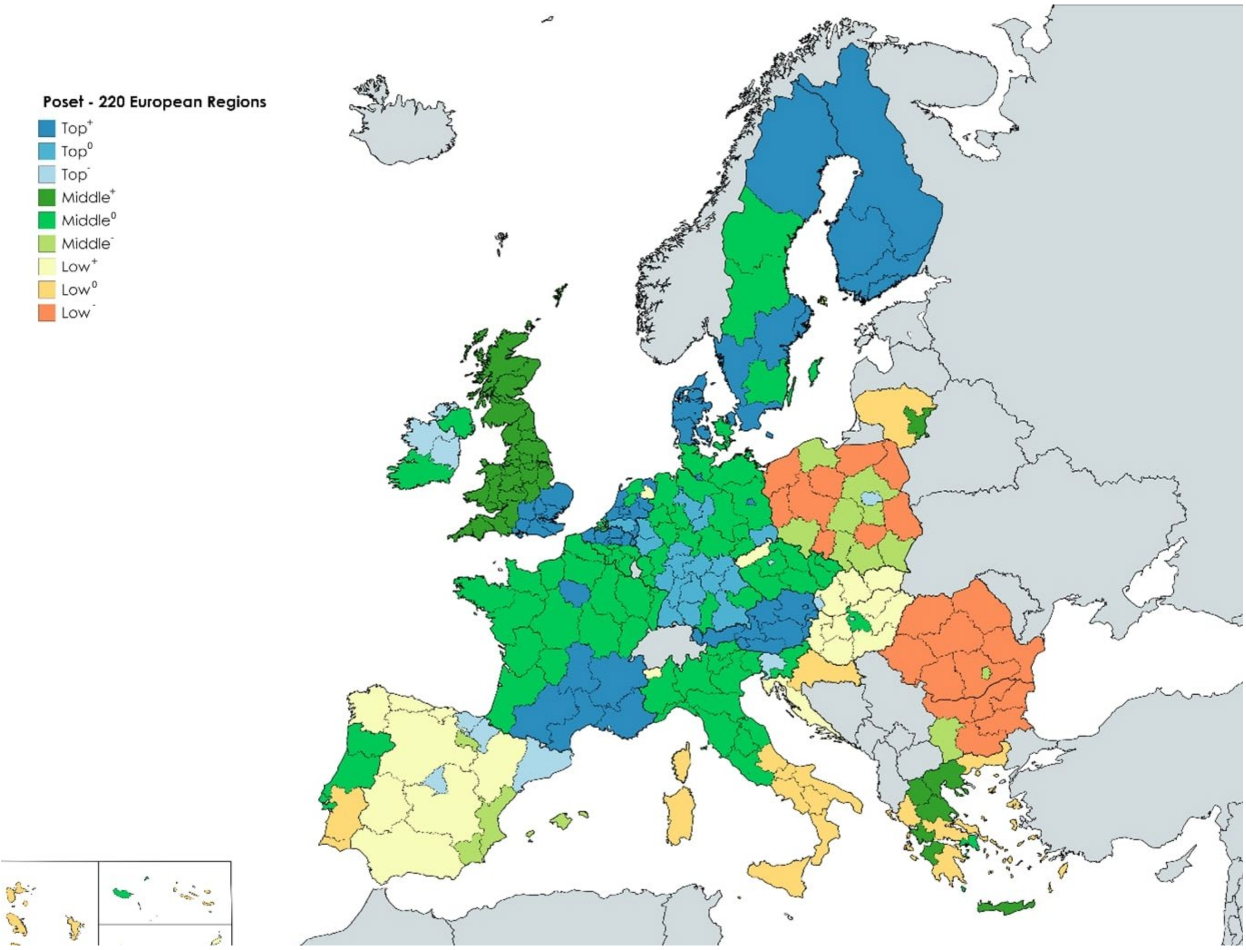
The top-performing regions in the 8-cluster analysis are the same as in the 11-cluster analysis. The regions classified as low performing in the 8-cluster analysis are the same as in the 11-cluster analysis. The middle-level regions in the 8-cluster analysis are the same as in the 11-cluster analysis, except for Åland, which is now included in the low-performing regions. Given that it is a one-of-a-kind case, it is not important for the general ranking. As a result, we can conclude that the results obtained are robust with regard to the choice of the number of clusters.

*4.5 Sublevels and charts*

In order to complete the analysis and display all the results in a political map of European regions, the last step is the definition of the three sublevels for each of the three performance groups already discussed. For the 64 regions in the top level, three sub-groups are identified as follows: the 35 regions in clusters 1 and 7 form the $top^{+}$ level, the 18 regions of cluster 8 compose the $top^{0}$ level, and finally the 11 regions of cluster 5 represent the $top^{-}$ level.

Regarding the middle level, it is easy to identify three subgroups, i.e. cluster 10 as $middle^{+}$, cluster 2 as $middle^{0}$, followed by cluster 4 as $middle^{-}$. In this level, we also find cluster 11 (the Finnish archipelago of Åland). Finally, concerning the low level, as it is formed by just three clusters already ranked after the first poset analysis, it is easy to assign cluster 6 as $low^{+}$, cluster 9 as $low^{0}$, and cluster 3 as $low^{-}$. In Figure 3, all regions are classified according to levels and sublevels.

*Figure 3 – Final chart representing the result of the poset-based analysis of 220 European regions*




In Figure 3, the top level is represented by regions in blue. The only country that has all its regions as top-performing is Austria. Moreover, the continental part of Finland belongs to this category as well as south-eastern England, southern France, southern Germany, some regions of north-eastern Spain, and most regions of Belgium, Denmark, Ireland, the Netherlands, and Sweden. A remarkably interesting aspect is the behaviour of the regions where the capital cities are located: 16 out of 23 of those regions belong to the top-level groups. Also, the capital cities of countries that are not considered as Innovation Leaders, such as the Czech Republic, Hungary, Poland, Slovakia, and Slovenia and are in top-level regions. The only countries that do not follow this pattern are Bulgaria, Croatia, Greece, Italy, Lithuania, Portugal, and Romania, but we have to keep in mind that for instance Lisbon, Rome and Zagreb are located in fairly large regions, whereas the majority of European capitals are in smaller regions and so they can concentrate all the assets in a high-density region.

The middle level (regions in green) is clearly represented by central Europe. In this category we can find most northern regions of several countries, such as France, Germany, Greece, Italy, Portugal, and the United Kingdom, as well as almost the entire Czech Republic and some regions of Poland. Furthermore, the capital cities of Bulgaria, Croatia, Greece, Italy, Lithuania, Portugal, and Romania belong to this level; as a result, no European capital is located in a low-level region.

The low level (from yellow, low$^{+}$, to red, low$^{-}$) is mostly composed of regions of southern Europe (most regions of Greece and Spain, southern Italy, southern Portugal) and central and eastern Europe (most regions of Bulgaria, Croatia, Hungary, Lithuania, Poland, and Romania). There are two isolated cases: one in northern Italy (Valle D'Aosta) and another one in the Netherlands (Drenthe). These two cases will be discussed in Section 4.6.

### *4.6 Poset-based ranking vs RIS 2019: a comparison*

A comparison of the results obtained by the poset-based analysis with the outcomes obtained by the Regional Innovation Scoreboard 2019 is shown in Table 2.

*Table 2 – A comparison between the composition of the performance groups in the RIS 2019 and in the poset-based analysis*

| *Performance groups* | ***poset Top level*** | ***poset Middle level*** | ***poset Low level*** |
|---|---|---|---|
| **RIS Innovation Leaders** | 100% | 0% | 0% |
| **RIS Strong Innovators** | 40% | 59% | 1% |
| **RIS Moderate Innovators** | 9% | 51% | 40% |
| **RIS Modest Innovators** | 0% | 3% | 97% |

Table 2 presents some significant findings. First, all regions in the Innovation Leaders group in the RIS 2019 belong to the top level in the poset-based analysis. Second, 99% of the regions belonging to the Strong Innovators group in the RIS 2019 are considered part of the top level or middle level in the poset-based analysis (just one region does not follow this pattern). Third, 91% of the Moderate Innovators regions of the RIS 2019 are placed in the middle or the low level in the poset-based analysis (only eight regions do not comply with this pattern). Finally, all regions except one belonging to the Modest Innovators group of the RIS 2019 are considered as low-level regions in the poset-based analysis as well. Hence, 210 out of 220 regions show the same classification (95.5% of the total). Only ten regions are ranked very differently. Among them, the most represented country is Spain, with four out of ten regions included.

As discussed above, the regions in which the capital city is located belong to the top or middle level, and in most cases show better results than the majority of the other regions in the same country. This aspect is also confirmed by looking at the ten regions mentioned above: half of them are regions in which the capital is located. Moreover, the Polish region of Mazowiecki is the region in which Warsaw is located. In addition, the Spanish region of Cataluña contains Barcelona, which is not the capital of Spain, but is a city with more than one and a half million inhabitants. Note that nine out of these ten regions improve their RIS 2019 ranking in the poset-based analysis, except for Drenthe in the Netherlands, which is classified as a Strong Innovator in the RIS 2019 but belongs to low-level cluster 6 according to the poset-based analysis. The reasons for this incongruity are to be found in cluster 6 and in the attribute-related sensitivity analysis: the reduction of the indicators applied to make it possible to obtain a poset, excluding from the final data matrix the indicators for which the cluster was a good performer. Moreover, both the dendrogram and the silhouette plot of cluster 6 show that Drenthe is one of the two regions that have fewer characteristics in common with the other 21 regions of cluster 6. Hence, cluster 6 is slightly penalised in the analysis and Drenthe is even more penalised.

Another region with the same characteristics as Drenthe is Valle D'Aosta, the only northern Italian region belonging to a low-level cluster. This confirms that it does not suffice in the poset-based analysis to obtain a 'good mean' score, but that it is fundamental not to be low performing on any attribute to avoid being downgraded in the ranking. To conclude this part, the only 10 regions that do not follow the pattern between the RIS 2019 and the poset-based analysis can clearly be explained.

## 5. Discussion and conclusions

The aim of this study was to provide an alternative analysis to measure the regional innovation performance of 220 European regions, starting from the data collected in the Regional Innovation Scoreboard 2019. As innovation is a complex issue, our main goal was to avoid the construction of the ranking of the analysed regions based on the simple arithmetic average of the normalised scores of the indicators and, thus, to provide a different point of view from the one suggested by the RIS 2019. First, the analysis presented shows that it is possible to adopt the poset-based approach in order to manage a large data matrix by reducing the number of objects through a cluster analysis and by considering only the indicators with the strongest impact detected through the attribute-related sensitivity analysis. Second, the poset-based approach implies that if a cluster is better ranked than another, it means that there are no indicators on which it has a lower score and, thus, that it provides a better performance. The information resulting from the cluster analysis could be interesting for stakeholders and policymakers to construct patterns of collaboration with other similar regions across Europe. In fact, the 220 European regions were grouped in 11 clusters, and the results revealed that the Innovation Leaders are regions located mostly in central and northern Europe, whereas the low-performing regions are located mainly in southern and eastern Europe. To facilitate an in-depth discussion of the results, we created nine different categories of outcomes (three for each performance level), identifying more detailed similarities among different European regions and clusters.

The attribute-related sensitivity analysis made it possible to detect the attributes with the strongest impact for categories with more than two indicators, namely ‘framework conditions’ and ‘innovation activities,’ which are *population aged 30-34 with tertiary education* and *lifelong learning* for the former, and *innovative SMEs collaborating with others* and *design applications* for the latter. Policymakers can therefore concentrate just on specific indicators in order to improve the ranking of the regions.

The innovation leaders identified in this analysis are the 35 regions classified as top$^+$, which is the combination of clusters 1 and 7, at the top of the ranking. They include two regions from Belgium (Région de Bruxelles Capitale and Vlaams Gewest), four from Denmark (Hovedstaden, Midtjylland, Nordjylland and Syddanmark), three from Germany (Berlin, Bremen and Hamburg), four from France (Auvergne–Rhône Alpes, Île de France, Languedoc-Roussillon–Midi-Pyrénées, Provence–Alpes–Côte d'Azur), seven from the Netherlands (Gelderland, Groningen, Limburg, Noord-Holland, Overijssel, Utrecht, Zuid-Holland), all the Austrian regions, all the Finnish regions (except for the one-of-a-kind archipelago of Åland), five regions from Sweden (Östra Mellansverige, Övre Norrland, Stockholm, Sydsverige, Västsverige) and three from the UK (East of England, London, and the South East).

Finally, we compared the results of the poset-based analysis with the four performance categories presented in the RIS 2019 and it was possible to identify similarities: top regions in the poset-based analysis are either Innovation Leaders or Strong Innovators in the RIS 2019; middle-level regions in our analysis are either Strong or Moderate Innovators in the RIS 2019. Last, the low-level regions in the poset-based analysis are either Moderate or Modest Innovators in the RIS 2019.

Only 10 regions are ranked very differently in the poset-based analysis compared to the RIS 2019: the majority are regions in which the capital is located (such as Bratislava, Budapest, Ljubljana, Madrid, and Warsaw) and are better ranked in the poset-based analysis compared to the RIS 2019. The only region that is worse ranked in the poset-based analysis is Drenthe (the Netherlands), mainly due to the fact that it is low performing on the indicators that have the strongest impact.

As the analysis included 220 European regions, it is not possible to use the results to establish a ranking of the regions within the same country, which could be of interest for policymakers. Hence, it could be interesting for future research to consider only the regions of a particular country adopting the approach discussed in this study. Another interesting investigation would be to perform the poset-based analysis at a country level by using the available data of the European Innovation Scoreboard. The results of the analysis at the regional level presented in this paper could be compared with the results of the analysis using national data of the 23 countries, which could be conducted adopting the method outlined in this study. It would be interesting to find further similarities.

## Appendix A

To better understand the characteristics of the theory of partially ordered sets, we provide a simple example as a guide for the analysis performed.

Consider four given objects a, b, c and d, and two attributes $q_1$ and $q_2$, as described in Table A.1. We will call the set of objects X, and the set of attributes A. In the table below, we provide an example in which we consider two numerical attributes in which the higher the score, the better the outcome; however, in poset theory, attributes are just features and they could also be linguistic descriptions (i.e. high, medium, low) or ordinal attributes.

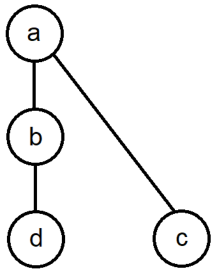
*Table A.1 – Example: dataset*

| Objects | $q_1$ | $q_2$ |
|---|---|---|
| a | 6 | 3 |
| b | 3 | 2 |
| c | 5 | 1 |
| d | 2 | 2 |

If we simply calculate the average of all indicators to determine the ranking, we will easily find that object a leads the ranking with a score of 4.5, followed by object c (3), and finally objects b and d (respectively with a score of 2.5 and 2). However, using the average may lead to wrong conclusions. In the poset this is avoided, since it is crucial to compare all the objects based on all attributes. Therefore, we could say that object a (6,3) is better than object b (3,2), object c (5,1) and object d (2,2) since it shows a higher score on both attributes. We could also say that object b is better than object d because even if the two objects tie on $q_2$ (2 for both objects b and d), object b has a higher score on $q_1$ compared to object d (3 for object b and 2 for object d). What is not possible to compare is object c with objects b and d: c shows a higher score on $q_1$ compared to both objects b and d ($5 > 3$ and $5 > 2$), but a worse score on $q_2$ ($1 < 2$); hence, object c is comparable with object a only and incomparable with objects b and d.

Looking at the dataset, we could then write the relationships between the comparable objects: $a > b > d$, as well as $a > c$. At the same time, we know that $c \parallel b$ and $c \parallel d$ (where $\parallel$ is the sign to represent incomparability). The result can be also represented through a Hasse diagram, as in the figure below.

*Figure A.1 – Example: Hasse diagram*




Now it is possible to identify the downset and the upset of any of the objects. The downset of an object $x$ consists of those objects $y$ such that $y \leq x$; its cardinality is denoted as D($x$). If $y < x$ for one or more indicators and $y > x$, then $x$ and $y$ are incomparable; the number of objects that are incomparable with an object $x$ is denoted as I($x$). We obtain Table A.2.

*Table A.2 – Example: downsets and incomparabilities of the objects, in numbers*

| Objects | D($x$) | I($x$) |
|---|---|---|
| a | 4 | 0 |
| b | 2 | 1 |
| c | 1 | 2 |
| d | 1 | 1 |

In Table A.2 it is possible to see, for instance, that the downset of object b consists of two objects (objects b and d).

We are now able to rank the objects of the poset. The method adopted is the so-called Local Partial Order Model (LPOM), where the 'final score' of an object is a function of D($x$) and I($x$). The formula to compute the 'final score' $\delta(x)$ of any object $x$ is [59]:

$$\delta(x) = \mathrm{D}(x)\,[(n+1)\;/\;(n+1-\mathrm{I}(x))] \quad \text{(A.1)}$$

where $x$ is the object of interest and $n$ indicates the total number of objects.

The number of the objects in this case is $n$ = 4. For instance, the score of object a, applying the formula, is: 4 * (4 + 1) / (4 + 1 – 0) = 4 * 5 / 5 = 4. After having computed the score for all the objects, we obtain the following ranking: *a, b, c, d*, which is different from the ranking obtained by simply calculating the average of the indicators, which in this case yields a, c, b, d. Hence, the Hasse diagram highlights which objects are without any doubt better (or worse) than the others. With the LPOM it is possible to rank all the objects, even if some of them are incomparable.

Finally, in the poset-based analysis, it is possible to reduce the number of attributes through the so-called 'attribute-related sensitivity analysis'. The aim is to examine how an attribute influences the position of the objects in the Hasse diagram by removing a column from the data matrix [57]. To better understand how the attribute-related sensitivity analysis works, we could add a third attribute, namely $q_3$ (see Table A.3) to the dataset we have analysed so far. The goal, now, is to find the pair of attributes (out of three) that permits to reproduce the original Hasse diagram of Figure A.1.

*Table A.3 – Example: dataset with three attributes*

| Objects | $q_1$ | $q_2$ | $q_3$ |
|---|---|---|---|
| a | 6 | 3 | 3 |
| b | 3 | 2 | 2 |
| c | 5 | 1 | 2 |
| d | 2 | 2 | 1 |

We first have to identify the downset of each object considering the whole data matrix (X, A). Then we compare these identified downsets with the ones of all objects (X) considering the same data matrix with the exclusion of one attribute at a time. To find, for instance, the impact of $q_1$, we have to look at the columns (X, A) and (X, A\\{$q_1$}) of Table A.4: for each object, we identify what are the downsets considering the two different data matrices. We can see in Table A.4 that the downset of object b in (X, A) consists of two objects (b and d), but it consists of three objects in (X, A\\{$q_1$}) (objects b, c and d). The total difference in cardinality between the two data matrices (counting the number of objects that form the downsets) is 1, as indicated in the last row of Table A.4. We then repeat the same exercise excluding indicators $q_2$ and $q_3$. The goal is to find the pair of attributes that allows to replicate the Hasse diagram of Figure A.1.

*Table A.4 – Example: attribute-related sensitivity analysis. Downsets of the objects in X for different subsets of attributes*

| Objects | (X, A) | (X, A\\{$q_1$}) | (X, A\\{$q_2$}) | (X, A\\{$q_3$}) |
|---|---|---|---|---|
| a | {a, b, c, d} | {a, b, c, d} | {a, b, c, d} | {a, b, c, d} |
| b | {b, d} | {b, c, d} | {b, d} | {b, d} |
| c | {c} | {c} | {b, c, d} | {c} |
| d | {d} | {d} | {d} | {d} |
| *Total difference in cardinality* | | 1 | 2 | 0 |

As shown in Table A.4, $q_3$ has no impact on the results, while excluding attribute $q_2$ results in two differences; in fact, without $q_2$, object c is higher than both objects b and d, which is not the case in the original data matrix (in Table A.4 the differences are marked in red). Finally, it is possible to conclude that the pair of attributes that best represents the original Hasse diagram is formed by $q_1$ and $q_2$, therefore if we want to simplify the data matrix, we can consider just the first two indicators.

## Appendix B

This appendix lists the 220 regions included in the study. Tables B.1 to B.4 represent the clusters of the top-performing level; Tables B.5 to B.8 represent clusters of the middle level; the clusters of the low-performing level are collected in Tables B.9 to B.11. The last column of the tables shows the performance category of the regions in the Regional Innovation Scoreboard 2019.

*Table B.1 – Top$^+$, Cluster n° 1 (1$^{st}$ position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Austria** | Ostösterreich | Strong Innovator |
| | Südösterreich | Strong Innovator |
| | Westösterreich | Strong Innovator |
| **Belgium** | Région de Bruxelles Capitale | Innovation Leader |
| | Vlaams Gewest | Strong Innovator |
| **Denmark** | Nordjylland | Strong Innovator |
| | Syddanmark | Strong Innovator |
| **Finland** | Etelä-Suomi | Innovation Leader |
| | Länsi-Suomi | Innovation Leader |
| | Pohjois-ja Itä Suomi | Strong Innovator |
| **France** | Auvergne – Rhône Alpes | Strong Innovator |
| | Île de France | Strong Innovator |
| | Languedoc-Roussillon – Midi-Pyrénées | Strong Innovator |
| | Provence Alpes Côte d'Azur | Strong Innovator |
| **Germany** | Berlin | Innovation Leader |
| | Bremen | Strong Innovator |
| | Hamburg | Innovation Leader |
| **Netherlands** | Gelderland | Strong Innovator |
| | Groningen | Strong Innovator |
| | Limburg | Strong Innovator |
| | Noord-Holland | Innovation Leader |
| | Overijssel | Strong Leader |

| | | |
|---|---|---|
| | Utrecht | Innovation Leader |
| | Zuid-Holland | Innovation Innovator |
| **Sweden** | Östra Mellansverige | Innovation Leader |
| | Övre Norrland | Strong Innovator |
| **United Kingdom** | East of England | Innovation Leader |
| | London | Innovation Leader |
| | South East | Innovation Leader |

*Table B.2 – Top$^+$, Cluster n° 7 (2nd position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Denmark** | Hovedstaden | Innovation Leader |
| | Midtjylland | Innovation Leader |
| **Finland** | Helsinki-Uusimaa | Innovation Leader |
| **Sweden** | Stockholm | Innovation Leader |
| | Sydsverige | Innovation Leader |
| | Västsverige | Innovation Leader |

*Table B.3 – Top$^0$, Cluster n° 8 (3rd position in the ranking, tie with cl. 5)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Germany** | Braunschweig | Innovation Leader |
| | Darmstadt | Innovation Leader |
| | Dresden | Innovation Leader |
| | Düsseldorf | Strong Innovator |
| | Freiburg | Innovation Leader |
| | Gießen | Strong Innovator |
| | Hannover | Strong Innovator |
| | Karlsruhe | Innovation Leader |
| | Köln | Strong Innovator |
| | Mittelfranken | Innovation Leader |
| | Oberbayern | Innovation Leader |
| | Oberfranken | Strong Innovator |
| | Oberpfalz | Strong Innovator |
| | Rheinhessen-Pfalz | Innovation Leader |
| | Stuttgart | Innovation Leader |
| | Tübingen | Innovation Leader |

| | | |
|---|---|---|
| | Unterfranken | Strong Innovator |
| **Netherlands** | Noord-Brabant | Innovation Leader |

*Table B.4 – Top⁻, Cluster n° 5 (3th position in the ranking, tie with cl. 8)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Czech Republic** | Praha | Strong Innovator |
| **Hungary** | Budapest | Moderate Innovator |
| **Ireland** | Eastern and Midland | Strong Innovator |
| | Northern and Western | Strong Innovator |
| **Poland** | Warszawski stołeczny | Moderate Innovator |
| **Slovakia** | Bratislavský kraj | Moderate Innovator |
| **Slovenia** | Zahodna Slovenija | Moderate Innovator |
| **Spain** | Cataluña | Moderate Innovator |
| | Comunidad de Madrid | Moderate Innovator |
| | Comunidad Foral de Navarra | Moderate Innovator |
| | País Vasco | Moderate Innovator |

*Table B.5 – Middle⁺, Cluster n° 10 (5th position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Greece** | Dytiki Ellada | Moderate Innovator |
| | Dytiki Makedonia | Moderate Innovator |
| | Kentriki Makedonia | Moderate Innovator |
| | Kriti | Strong Innovator |
| | Thessalia | Moderate Innovator |
| **Lithuania** | Sostinės regionas | Moderate Innovator |
| **United Kingdom** | East Midlands | Strong Innovator |
| | North East | Strong Innovator |
| | North West | Strong Innovator |
| | Scotland | Strong Innovator |
| | South West | Strong Innovator |
| | Wales | Strong Innovator |
| | West Midlands | Strong Innovator |
| | Yorkshire and The Humber | Strong Innovator |

*Table B.6 – Middle[0], Cluster n°2 (6th position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Belgium** | Région Wallonne | Strong Innovator |
| **Czech Republic** | Jihovýchod | Moderate Innovator |
| | Jihozápad | Moderate Innovator |
| | Moravskoslezsko | Moderate Innovator |
| | Severovýchod | Moderate Innovator |
| | Strední Cechy | Moderate Innovator |
| | Strední Morava | Moderate Innovator |
| **Denmark** | Sjælland | Strong Innovator |
| **France** | Alsace Champagne Ardenne Lorraine | Strong Innovator |
| | Aquitaine Limousin Poitou Charentes | Strong Innovator |
| | Bourgogne - Franche Comté | Strong Innovator |
| | Bretagne | Strong Innovator |
| | Centre - Val de Loire | Strong Innovator |
| | NordPas de Calais - Picardie | Moderate Innovator |
| | Normandie | Moderate Innovator |
| | Pays de la Loire | Strong Innovator |
| **Germany** | Arnsberg | Strong Innovator |
| | Brandenburg | Strong Innovator |
| | Chemnitz | Strong Innovator |
| | Detmold | Strong Innovator |
| | Kassel | Strong Innovator |
| | Koblenz | Moderate Innovator |
| | Leipzig | Strong Innovator |
| | Lüneburg | Moderate Innovator |
| | Mecklenburg-Vorpommern | Strong Innovator |
| | Münster | Strong Innovator |
| | Niederbayern | Moderate Innovator |
| | Saarland | Strong Innovator |
| | Sachsen-Anhalt | Strong Innovator |
| | Schleswig-Holstein | Strong Innovator |
| | Schwaben | Strong Innovator |
| | Thüringen | Strong Innovator |
| | Trier | Strong Innovator |

| | | |
|---|---|---|
| | Weser-Ems | Moderate Innovator |
| **Greece** | Attiki | Moderate Innovator |
| **Hungary** | Pest | Moderate Innovator |
| **Ireland** | Southern | Strong Innovator |
| **Italy** | Emilia-Romagna | Moderate Innovator |
| | Friuli-Venezia Giulia | Strong Innovator |
| | Lazio | Moderate Innovator |
| | Liguria | Moderate Innovator |
| | Lombardia | Moderate Innovator |
| | Marche | Moderate Innovator |
| | Piemonte | Moderate Innovator |
| | Provincia Autonoma Bolzano | Moderate Innovator |
| | Provincia Autonoma Trento | Moderate Innovator |
| | Toscana | Moderate Innovator |
| | Umbria | Moderate Innovator |
| | Veneto | Moderate Innovator |
| **Netherlands** | Flevoland | Strong Innovator |
| | Friesland | Moderate Innovator |
| | Zeeland | Moderate Innovator |
| **Portugal** | Centro | Strong Innovator |
| | Lisboa | Strong Innovator |
| | Norte | Strong Innovator |
| | Região Autónoma da Madeira | Moderate Innovator |
| **Slovenia** | Vzhodna Slovenija | Moderate Innovator |
| **Sweden** | Mellersta Norrland | Moderate Innovator |
| | Norra Mellansverige | Strong Innovator |
| | Småland med öarna | Strong Innovator |
| **United Kingdom** | Northern Ireland | Strong Innovator |

*Table B.7 – Middle⁻, Cluster n°11 (7th position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Finland** | Åland | Moderate Innovator |

*Table B.8 – Middle$^{-}$, Cluster n°4 ($8^{th}$ position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Bulgaria** | Yugozapaden | Moderate Innovator |
| **Poland** | Dolnoslaskie | Moderate Innovator |
| | Lódzkie | Moderate Innovator |
| | Malopolskie | Moderate Innovator |
| | Mazowiecki regionalny | Modest Innovator |
| | Podkarpackie | Moderate Innovator |
| | Pomorskie | Moderate Innovator |
| | Slaskie | Moderate Innovator |
| **Romania** | Bucuresti - Ilfov | Moderate Innovator |
| **Spain** | Comunidad Valenciana | Moderate Innovator |
| | Illes Balears | Moderate Innovator |
| | La Rioja | Moderate Innovator |
| | Región de Murcia | Moderate Innovator |

*Table B.9 – Low$^{+}$, Cluster n°6 ($9^{th}$ position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Croatia** | Jadranska Hrvatska | Modest Innovator |
| **Czech Republic** | Severozápad | Moderate Innovator |
| **Hungary** | Dél-Alföld | Moderate Innovator |
| | Dél-Dunántúl | Moderate Innovator |
| | Észak-Alföld | Modest Innovator |
| | Észak-Magyarország | Moderate Innovator |
| | Közép-Dunántúl | Moderate Innovator |
| | Nyugat-Dunántúl | Moderate Innovator |
| **Italy** | Valle d'Aosta | Moderate Innovator |
| **Netherlands** | Drenthe | Strong Innovator |
| **Slovakia** | Stredné Slovensko | Moderate Innovator |
| | Východné Slovensko | Moderate Innovator |
| | Západné Slovensko | Moderate Innovator |

| | | |
|---|---|---|
| **Spain** | Andalucía | Moderate Innovator |
| | Aragón | Moderate Innovator |
| | Canarias | Modest Innovator |
| | Cantabria | Moderate Innovator |
| | Castilla La Mancha | Modest Innovator |
| | Castilla y León | Moderate Innovator |
| | Ciudad Autónoma de Melilla | Modest Innovator |
| | Extremadura | Modest Innovator |
| | Galicia | Moderate Innovator |
| | Principado de Asturias | Moderate Innovator |

*Table B.10 – Low$^{0}$, Cluster n°9 (10$^{th}$ position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Croatia** | Kontinentalna Hrvatska | Moderate Innovator |
| **France** | Corse | Moderate Innovator |
| | Régions ultrapériphériques françaises | Moderate Innovator |
| **Greece** | Anatoliki Makedonia, Thraki | Moderate Innovator |
| | Ionia Nisia | Moderate Innovator |
| | Ipeiros | Moderate Innovator |
| | Notio Aigaio | Modest Innovator |
| | Peloponnisos | Moderate Innovator |
| | Sterea Ellada | Moderate Innovator |
| | Voreio Aigaio | Moderate Innovator |
| **Italy** | Abruzzo | Moderate Innovator |
| | Basilicata | Moderate Innovator |
| | Calabria | Moderate Innovator |
| | Campania | Moderate Innovator |
| | Molise | Moderate Innovator |
| | Puglia | Moderate Innovator |
| | Sardegna | Moderate Innovator |
| | Sicilia | Moderate Innovator |
| **Lithuania** | Vidurio ir vakaru Lietuvos regionas | Moderate Innovator |
| **Portugal** | Alentejo | Moderate Innovator |
| | Algarve | Moderate Innovator |
| | Região Autónoma dos Açores | Moderate Innovator |

*Table B.11 – Low⁻, Cluster n°3 (11th position in the ranking)*

| Country | Region | RIS 2019 classification |
|---|---|---|
| **Bulgaria** | Severe tsentralen | Modest Innovator |
| | Severoiztochen | Modest Innovator |
| | Severozapaden | Modest Innovator |
| | Yugoiztochen | Modest Innovator |
| | Yuzhen tsentralen | Modest Innovator |
| **Poland** | Kujawsko-Pomorskie | Modest Innovator |
| | Lubelskie | Modest Innovator |
| | Lubuskie | Modest Innovator |
| | Opolskie | Modest Innovator |
| | Podlaskie | Modest Innovator |
| | Swietokrzyskie | Modest Innovator |
| | Warminsko-Mazurskie | Modest Innovator |
| | Wielkopolskie | Moderate Innovator |
| | Zachodniopomorskie | Modest Innovator |
| **Romania** | Centru | Modest Innovator |
| | Nord-Est | Modest Innovator |
| | Nord-Vest | Modest Innovator |
| | Sud-Est | Modest Innovator |
| | Sud-Muntenia | Modest Innovator |
| | Sud-Vest Oltenia | Modest Innovator |
| | Vest | Modest Innovator |
| **Spain** | Ciudad Autónoma de Ceuta | Modest Innovator |

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