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Evaluating the efficiency of regional innovation systems in Europe: DEA approach

Abstract

For many years, regional innovation systems in Europe have been studied and compared against each other within the framework of the Regional Innovation Scoreboard. However, it has a number of drawbacks, e.g. the combined input-output approach, which does not respond to societal expectations, as in this era of all-round economisation, it is the outputs of the activity that are more important than the potential contained in the inputs. Therefore, in our study we focused on an approach aimed at maximising the outputs achieved by regional innovation systems. The results of the study indicated that, even taking into account negative environmental outcomes, the vast majority of regional innovation systems show efficiency. We have shown that although the regional innovation systems group studied is highly efficient, our research indicates that in the long term, the narrow classification into four innovation groups according to the Regional Innovation Scoreboard methodology is increasingly less useful, as there is a reduction in the number of groups as a result of the 'shift' of units to three main ones. We also provided recommendations for EU regional innovation policy on the Regional Innovation Scoreboard tool. Our recommendation is to introduce more differentiated variables into the European survey and to focus more on evaluating the innovation system from the perspective of the results obtained and less on an input approach.

Keywords: regional innovation systems, efficiency, Europe, DEA.

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Ocena efektywności regionalnych systemów innowacji w Europie: podejście DEA

Abstrakt

Od wielu lat regionalne systemy innowacji w Europie są badane i porównywane ze sobą w ramach Regional Innovation Scoreboard. Ma ona jednak szereg wad, np. podejście łączące nakłady i wyniki, które nie odpowiada oczekiwaniom społecznym, ponieważ w erze wszechstronnej ekonomizacji to wyniki działalności są ważniejsze niż potencjał zawarty w nakładach. Dlatego w naszym badaniu skupiliśmy się na podejściu mającym na celu maksymalizację wyników osiąganych przez regionalne systemy innowacji. Wyniki badania wskazały, że nawet biorąc pod uwagę negatywne skutki środowiskowe, zdecydowana większość regionalnych systemów innowacji wykazuje się efektywnością. Wykazaliśmy, że chociaż badana grupa regionalnych systemów innowacji jest wysoce wydajna, nasze badania wskazują, że w dłuższej perspektywie wąska klasyfikacja na cztery grupy innowacji zgodnie z metodologią Regional Innovation Scoreboard jest coraz mniej użyteczna, ponieważ następuje zmniejszenie liczby grup w wyniku „przesunięcia" jednostek do trzech głównych. Przedstawiliśmy również zalecenia dla regionalnej polityki innowacji UE dotyczące narzędzia Regional Innovation Scoreboard. Naszym zaleceniem jest wprowadzenie bardziej zróżnicowanych zmiennych do europejskiego badania i skupienie się bardziej na ocenie systemu innowacji z perspektywy uzyskanych wyników, a mniej na podejściu wejściowym.

Słowa kluczowe: regionalne systemy innowacyjne, efektywność, Europa, DEA.

INTRODUCTION

Innovation processes aiming to create new products, services, technological, marketing or organisational solutions occur in specific environments. They use networks of linkages and couplings that can be called innovation systems. Interest in assessing the efficiency and productivity of regional innovation systems (RIS) has been growing for more than two decades. On the one hand, this is the result of the proliferation of the concept of a systems view of innovation processes in the literature since the late 1980s (e.g. Freeman, 1987; Lundvall, ed. 1992; Patel, Pavitt, 1994), followed by research on RIS since the mid-1990s. (Wiig, Wood, 1995; Howells, 1999; Doloreux, Parto, 2005). They pointed out that the regional dimension is crucial for systemic innovation processes. In this context, RIS is the totality of the links and interactions occurring in knowledge creation, application and dissemination between the public and private sectors represented by formal institutions and other organisations operating according to the prevailing institutional order (Doloreux, Parto, 2005). On the other hand, the growing interest in the effectiveness of RIS has been influenced by the development of the triple helix concept developed by Etzkowitz and Leydersorff (1996) and its modifications in the form of the quadruple and quintuple helix model (Carayannis, Campbell, 2009; Carayannis et al., 2012). The authors mentioned above understood the regional innovation system as a flexible, creative, socio-economic and synergistic system of linkages between the various actors involved in innovation processes in a specific territory. The interactions between actors from the scientific sphere, the R&D sector, manufacturing and service companies, innovation and technology transfer support institutions and public authorities (local and regional) create the conditions for entrepreneurship, innovation growth and economic development in the region. This assumption leads to the concept of innovation ecosystem (IE) which Granstrand and Holgersson (2020, p. 3) is defined by "the evolving set of actors, activities, and artifacts, and the institutions and relations, including complementary and substitute relations, that are important for the innovative performance of an actor or a population of actors". The IE concept can occur at different structural levels, whether, local, regional or national. It is worth noting that the IE concept is now widely supported by the EU, under the New European Innovation Agenda. A new wave of deep technological innovation has prompted a new agenda as response to reducing greenhouse gas emissions (European Commission, 2022b). The European Innovation Ecosystems (EIE) programme was developed to create more connected, inclusive, and efficient innovation ecosystems (European Innovation Council and SMEs Executive Agency, 2023). A study by Stojčić (2021) shows that if units collaborate with entities from other EU countries, then there is an easier commercialisation of already existing products. In the case of incremental and radical innovations, it is much more beneficial to work with partners from the US, China and India to commercialise the product.

Rong *et al.* (2020) emphasise that unlike RIS, which mainly focused on a static view of one's own activities and skills in one's own regions, regional IE focuses more on the dynamics of different forms of cooperation (within the region and between different regions) and co-evolution to achieve continuous innovation and development.

The experience of many countries with the use of three types of RIS (knowledge clusters, industrial production zones and non-science and technology-based regions) (Ajmone Marsan, Maguire, 2011) and the results of comparative studies of such RIS in OECD countries (Weresa, 2012), Latin America (Cario et al., 2023), among others, indicate that there are many determinants of a region's innovation capacity and position. These have an impact on the greater or lesser efficiency of RIS.

In the third decade of the 21st century, this research problem is becoming increasingly relevant due to the intensifying development challenges that have technological, economic, environmental, social, demographic and even military and geopolitical dimensions. These challenges are forcing an energy and environmental transformation, but also a remodelling of the global economy towards the digital. Knowledge, technology and innovation are among the most critical factors determining the development and competitiveness of businesses, economies, regions and local communities. These arise in the region due to interaction, collective, and networked innovation processes based on personal and institutional linkages between the actors of these processes. Understanding and assessing the level of efficiency and productivity of RIS and identifying the reasons for interregional differences in this respect is cognitively valuable. In addition, it has a utilitarian value in that it allows recommendations to be made for improving the Regional Innovation Scoreboard in Europe (RISiE) tool. It is a regional extension of the European Innovation Scoreboard (EIS) and provides an assessment of the innovation performance of European regions using a limited number of input and output indicators. The paper outlines the current limitations of the RISiE indicators that are used to assess the innovation performance of regions in Europe.

The above arguments led the authors of this study to undertake two research objectives: (1) to measure and evaluate the efficiency of RIS in Europe having regard to environmental conditions at the NUTS-2 level in period 2014–2021 and (2) to provide recommendations for the EU's regional innovation policy on the EIS-RISiE tool.

In order to achieve this, the authors used various research methods, such as a literature study, Data Envelopment Analysis (DEA) models. In addition, they used general methods (inductive inference and synthesis). In the first stage of the study, the non-radial slacks-based measure (SBM) with undesirable output model will be used to divide the units into efficient and inefficient ones. In the second stage, a ranking will be made based on the non-radial Super-SBM model with undesirable output. Compared to previous studies undertaken in the literature, this study not only assesses the level of efficiency as in another study but also identifies the best units on which less efficient RIS should be modelled. This has been significantly lacking in European research. The conducted research also made it possible to demonstrate whether changes in efficiency translated into a real increase in productivity of the same units. Only such a two-stage research approach, significantly extending previous research, provides a comprehensive knowledge of RIS in Europe. In order to conduct the research, they used data from the RISiE reports for the period 2014–2021. Earlier studies undertaken in the literature consider a much older period and are only a single-aspect analysis, compared to this one, which uses both the two research stages and, and takes into account environmental conditions. Our study aims, on the one hand, to test the usability of the RIS assessment variables and the RISiE tool itself, considering an approach focused on maximising RIS scores, using a two-stage research process. On the other hand, on the basis of the research results obtained and the literature review, our aim is to formulate recommendations to enable the improvements we believe are necessary, in terms of RISiE usability.

The added value of the study is, firstly, to take environmental factors into account when analysing the innovation system, like any other production process that uses environmental resources and generates negative environmental factors. This study considers the perspective of assessing innovation in relation to the environment that can be found in the work of Xu *et al.* (2019, 2020), Stergiou *et al.* (2024) and Łącka and Brzezicki (2022). Secondly, it analyses the RIS sample over a longer period of time than usually one or a few years, so that changes in regional innovation can be assessed in a more controlled way than in the case of changes in the number of units surveyed. Thirdly, the study points out that the input-output approach of the EIS is not appropriate for public expectations. It is more important to take an output-oriented approach to the innovation system rather than a resource-oriented approach, which may be significant but does not necessarily translate into expected effects that impact society and the economy.

The article is structured as follows. After the introduction in section 2, the authors reviewed the literature on the subject. In section 3, they discuss the research methodology and data sources. Section 4 contains the empirical findings and discussion. Section 5, presents the research conclusions, and Section 6 presents recommendations for EU's regional innovation policy on the EIS-RISiE tool.

Literature review

The variation in regional innovation in OECD countries, the European Union, China (Wang et al., 2015; Pan et al., 2023), Brazil (Alemida et al., 2023) or India (Malik et al., 2021) demonstrates that individual regional innovation systems show different capacities to achieve innovation under modern economic conditions. It is influenced by the differential efficiency of these structures to stimulate innovation. The literature review by López-Rubio *et al.* (2020) shows that more and more studies on RIS are being produced yearly. Most deal with theoretical rather than empirical aspects (Ribeiro et al., 2023). However, it should be noted that few studies have been conducted using the nonparametric DEA method (Brzezicki, 2024). Studies can be divided into two main groups:

1. estimating the efficiency of RIS in a given country (Kaihua, Mingting, 2014),
2. efficiency analyses in a broader scope considering RIS in different countries, e.g. European countries (Aristovnik, 2014).

When examining the efficiency of RIS in a particular country, data available in the country under study were mainly considered (Ciołek, Golejewska, 2022). In contrast, such studies for RIS in Europe mostly used RISiE data (Teirlinck, Spithoven, 2023) or Eurostat database (Stergiou et al., 2024). The authors noted that during such studies, researchers did not use all variables available in the RISiE (Carayannis et al., 2015; Teirlinck, Spithoven, 2023). As a result, the informative scope of the study is considerably limited, and the possibilities of multivariate analysis through the DEA method are not fully exploited. An analysis of the literature shows that no one-size-fits-all set of variables is considered when estimating efficiency, although some variables are used more frequently than others (e.g. number of patents, R&D expenditure). It is also worth noting the limitations of the DEA method, which estimates efficiency relative to the whole sample. Changing the number of units surveyed can alter efficiency ratios from year to year. In the study by Zabala-Iturriagagoitia *et al*. (2007) the efficiency of RIS was measured for 161 regions in 2002 and 187 in 2003. In this case, it was impossible to compare efficiency indicators between the years of the study. Researchers analysing RIS in a given country (China, Poland, Germany) took from 30 (Wang, Zhang, 2022) to 72 (Ciołek, Golejewska, 2022) and even up to 150 territorial units (Broekel et al., 2018; Stergiou et al., 2024). On the other hand, Zabala-Iturriagagoitia *et al*. (2007), Carayannis *et al.* (2015), Teirlinck and Khoshnevis (2022), Aristovnik (2014), Teirlinck and Spithoven (2023) in the case of a study of the efficiency of RIS in Europe assumed a different number, which depended on the occurrence of RIS units in a given European study (RISiE), but also on the availability and completeness of data. Between 161 and 265 regions (NUTS-2) were therefore included in the analyses. However, most RIS studies focus on a selected country rather than analysing several countries (e.g. within Europe).

Brzezicki (2024) noted that, to date, one of three analytical options had been chiefly used when tackling the accepted research problem: either classical DEA models have been used to estimate efficiency, super-efficiency DEA models have been used to determine the ranking of efficient facilities or the Malmquist index has been used to measure productivity changes over time and identify its determinants. Few studies consider the two analytical methods together (Chen, Guan, 2012; Han et al., 2016; Broekel et al., 2018). Most commonly, the efficiency of RIS has been measured using different DEA models. Few studies used the DEA model with super-efficiency (e.g. Chen, Guan, 2012; Han et al., 2016; Xu et al., 2020), and occasionally the Malmquist index (e.g. Han et al., 2016; Broekel et al., 2018). The authors also noted that mostly simple radial DEA models were used for the analyses (Zabala-Iturriagagoitia et al., 2007; Dzemydaitė et al., 2016; Vechkinzova et al., 2019), which are characterised by proportionality of input decrease or output increase. Only in a few cases has a different model been applied. Cao *et al.* (2023) used a two-stage model to estimate the efficiency of RIS in 30 provinces in China, and Teirlinck and Spithoven (2023) used a non-radial SBM dynamic model to measure the efficiency of RIS in 207 European regions. Teirlinck and Spithoven (2023) show that scale-based performance classification inadequately reflects differences in efficiency in transforming knowledge inputs into innovation outputs. The use of DEA models in RIS studies to date (especially in Europe, and to a lesser extent in other countries, most minor in China) indicates that the authors of the analyses have not fully exploited the potential of these models. They have not determined the nature of the intermediate variable in network models, dynamic models or the specific output variable. In a study of China's innovation system, Xu *et al.* (2019) used a non-radial SBM model with undesirable outputs (CO_2 and SO_2 emissions). They argued that innovation development should affect the Sustainable Development Goals (SDGs). Therefore, atmospheric greenhouse gas (GHG) emissions should be included in the analysis. Stergiou *et al.* (2024) used a two-stage non-radial directional distance function (DDF) with undesirable output (CO_2 emissions) to measure inefficiency of innovation in 199 regions (NUTS 2 level) from 22 European countries, over the 2000–2018 period. They used only 10 variables from Eurostat database for the study. Stergiou *et al.* (2024) indicate that the inclusion of additional undesirable outputs in production activities can be considered fruitful directions for further research. In the subsequent study, Xu *et al.* (2020) used a non-radial Super-SBM model with undesirable outputs (CO_2 and SO_2 emissions) to measure the RIS in China. Unfortunately, the authors have not used this research approach in previous European RIS studies. In contrast, Xu *et al.* (2023a) used it to study the efficiency of the National Innovation System (NIS) in Europe. An interesting study was conducted by You and Teirlinck (2024), who analysed the impact of specialisation and diversification on regional R&D performance in China, Europe and the US.

The literature review conducted by Brzezicki (2024) revealed the following knowledge gaps: (1) lack of European studies using the Super-SBM model to rank efficient RIS (2) the capabilities of DEA models in determining the nature of variables (good vs. wrong outputs), (3) European studies conducted using DEA end in 2019 – no more recent data in the analyses (4) a small number of variables were used when estimating efficiency using DEA, (5) failure to take pollution variables into account. Therefore, the authors felt that a study was warranted to fill the gaps found in the literature.

Research methodology

The DEA method is used to study the efficiency of innovation systems, as noted in the previous section of this article. It was developed to measure the relative efficiency of decision-making units (DMUs) when considering multiple inputs and outputs. The origins of the DEA method can be traced back to an article by Charnes *et al.* (1978), in which the authors presented the first model (called CCR after the initials of their names: Charnes, Cooper & Rhodes), assuming constant returns to scale. Later, Banker *et al.* (1984) presented a second BCC (Banker, Charnes & Cooper) model, which assumed variable returns to scale. The above models only measure radial efficiency, i.e. a proportional reduction in inputs (input orientation) or a proportional increase in the performance of an entity (output orientation) relative to other entities in the sample group. In business practice, however, different inputs or outputs do not always affect the efficiency level of an economic entity to the same extent (Johnes, Tone, 2017). Therefore, Tone (2001) presented the SBM model based on non-radial efficiency, assuming that individual inputs and outputs have a differential impact on the efficiency level. Achieving the total efficiency level (100% or 1.0 score) is possible with different combinations of inputs or outputs.

The classic SBM model and others, e.g., CCR and BCC, make it possible to determine the unit's efficiency under study based on an efficiency criterion. It assumes that producing more products with fewer resources is better than generating fewer products. However, almost every human activity, in addition to producing the desired results of the activity, is also associated with the generation of undesired outputs (e.g. defective products, air pollution, water pollution, congestion, etc.). It is particularly noticeable in industrial production, energy and transport, where negative externalities (undesirable outputs) affecting the environment are generated. The above assumption is analytically transformed in the new model called SBM with undesirable outputs (Cooper et al., 2007). According to the assumption, the more efficient DMU will be the one whose production technology allows it to generate more good outputs consistent with expectations and fewer undesirable outputs in the form of final but incomplete products or negative externalities using fewer resources. The above assumption defines the definition of efficiency adopted in this study, which explicitly states the assumption of the output-oriented DEA model.

As the DEA method generates efficiency scores equal to unity for several DMUs included in the study, it is impossible to determine the most efficient one. The solution is to use a DEA model with super-efficiency. It generates efficiency scores above unity for those units that obtained efficiency equal to unity in the ordinary DEA model (Emrouznejad et al., 2025). Other results less than unity remain unchanged. The above assumption has also been implemented in the SBM model, as Tone (2002) developed his initial SBM model (Tone, 2001) with super-efficiency.

The authors decided to adapt for this study the comprehensive two-stage research approach (i.e., measure efficiency, creation of ranking efficiency) from three-stage proposed by Łącka and Brzezicki (2021), extending it with an SBM model with undesirable outputs. Each study stage has a different research objective (Table 1).

Table 1. Stages of the empirical study

Specification	Stage 1 study	Stage 2 study
Model	Non-radial SBM with undesirable output	Non-radial Super-SBM with undesirable output
Orientation Model	Output	
Returns to Scale in Model	Constant	
Number of DMUs (NUTS-2)	146	
Number of Inputs	8	
Number of Outputs	12	
Number of Periods	8	
Periods	2014–2021	
Source of data	European Commission (2022a)	
Goal of the stage	Estimation of the efficiency of the NUTS-2 studied: • NUTS-2 division into efficient and inefficient	Identification of the efficiency ranking of the studied NUTS-2: • identification of the most and least efficient NUTS-2 • dividing NUTS-2 into innovation groups
Research questions	Q1	Q2, Q3

Source: own elaboration

It was decided to use SBM models with undesirable outputs by adopting the research concept proposed by Xu *et al*. (2019) and Super-SBM models with undesirable outputs (Xu et al., 2020) during the Chinese RIS study. Unlike their research on NIS in Europe at the country level, we focused on RIS considering European territorial units at the NUTS-2 level in this study. Despite a wide variety of studies in many respects (e.g. model adopted, variables, research period, units covered), there are still research gaps in the topic under discussion. Many studies focus primarily on one aspect of the analysis (either estimating efficiency or ranking efficient units or determining productivity changes), with few considering two aspects simultaneously (e.g. Broekel et al.; 2018, Han et al. 2016; Foddi, Usai, 2013; Chen, Guan, 2012). However, no studies have been found in the literature that consider these two research steps together in Europe, analysing RIS efficiency and making ranking efficiency in a comprehensive manner.

In the first step, based on the SBM model with undesirable outputs, the efficiency level will be estimated, based on which NUTS-2 will be divided into efficient and inefficient regions. In the second stage, based on the Super-SBM model with undesirable outputs, a ranking of NUTS-2 will be made, and the most efficient and least efficient units will be identified. The MaxDEA programme was used for the calculations at each stage of the study. The objectives of the two stages are designed to provide answers to research questions:

Q1 Are there more than 75% of surveyed units in the research sample are efficient in orienting to the outputs in the model in each year when considering multiple variables and the environmental factor?

Q2 Is there a clear leader who is the most efficient in each year indicating, on the one hand, that it has such a huge competitive advantage over other units and, on the other hand, that there is a constant number of variables determining high efficiency?

Q3 Is there a narrow classification of efficiency groups according to the EIS methodology means there a reduction in the number of groups over the long term?

The above research questions follow directly from the research strategy adopted. At the outset, it was decided to test whether the variables included in the EIS-RISiE study would allow the community to be divided into efficient and inefficient units. If there were many more efficient units than inefficient ones, this would indicate that the variables have relatively little information value, as most RIS are characterised by a similar state of development. It was then concluded that it should be examined whether the most efficient unit or a small group of very efficient RIS could be extracted from the efficient units, and from which other inefficient units could follow. It was also considered whether there is a unit that differs significantly from the others and has such a huge competitive advantage in terms of innovation that its way of working and resources could be a good practice for other efficient units in the long-term. It was then decided to test the classification of groups according to the EIS methodology. It was sought to see whether such a narrow classification into four groups would not be reduced over time by the fact that units would perform better and better and eventually the vast majority would be in the top two or three groups.

Since the aim of innovation systems, regardless of their scope or structural level, is to create as many outputs as possible, the authors assumed that the DEA models would be output-oriented in this study. They obtained data for the study from the RISiE, a regional extension of the European Innovation Scoreboard (EIS). This report provides an assessment of the innovativeness of European regions based on a limited number of indicators. There are 20 indicators available at the regional level (European Commission, 2022a), which the authors decided to use in full in this study (Table 2).

Table 2. Output and input data assumed for the research

	Variable	RISiE	Reference
Input	x_1: Percentage of population aged 25–34 having completed tertiary education	x_1: 1.1.2	[6], [7]*, [8], [9]
	x_2: Lifelong learning, the share of population aged 25–64 enrolled in education or training aimed at improving knowledge, skills and competences	x_2: 1.1.3	[6], [9]
	x_3: Individuals who have above basic overall digital skills	x_3: 1.3.2	
	x_4: R&D expenditure in the public sector as percentage of GDP	x_4: 2.1.1	[6], [9]
	x_5: R&D expenditure in the business sector as percentage of GDP	x_5: 2.2.1	[1], [2], [6], [9]
	x_6: Non-R&D innovation expenditures as percentage of total turnover	x_6: 2.2.2	[1], [2], [6], [8]
	x_7: Innovation expenditures per person employed in innovation-active enterprises	x_7: 2.2.3	
	x_8: Innovative SMEs collaborating with others as percentage of SMEs	x_8: 3.2.1	[6], [8]
Output	y_1: International scientific co-publications per million population	y_1: 1.2.1	[6]
	y_2: Scientific publications among the top 10% most cited publications worldwide as percentage of total scientific publications of the country	y_2: 1.2.2	[6]
	y_3: SMEs introducing product innovations as percentage of SMEs	y_3: 3.1.1	[1], [4], [8]
	y_4: SMEs introducing business process innovations as percentage of SMEs	y_4: 3.1.2	[1], [8]
	y_5: Public-private co-publications per million population	y_5: 3.2.2	[6], [8]
	y_6: PCT patent applications per billion GDP (in Purchasing Power standards)	y_6: 3.3.1	[1], [2], [6], [7], [9]
	y_7: Trademark applications per billion GDP (in Purchasing Power standards)	y_7: 3.3.2	[1], [2], [6]
	y_8: Individual design applications per billion GDP (in Purchasing Power standards)	y_8: 3.3.3	[1], [2], [6]
	y_9: Employment in knowledge-intensive activities as percentage of total employment	y_9: 4.1.1	[1], [2], [6], [7], [8]
	y_{10}: Employment in innovative enterprises	y_{10}: 4.1.2	[3]
	y_{11}: Sales of new-to-market and new-to-enterprise product innovations as percentage of total turnover	y_{11}: 4.2.3	[2], [3], [4], [5], [6], [8]
	y_{12}: Air emissions in fine particulates (PM2.5) in Industry	y_{12}: 4.3.2	[4]*, [5]*

Note: [1] – Teirlinck, Spithoven (2023), [2] – Teirlinck, Khoshnevis (2022), [3] – Alarcón-Martínez *et al.*, (2023), [4] – Xu *et al.,* (2020), [5] – Xu *et al.,* (2019), [6] – Łącka, Brzezicki (2021), [7] – Dzemydaitė *et al.,* (2016), [8] – Carayannis *et al.,* (2015), [9] – Zabala-Iturriagagoitia *et al.*, (2007), * – similar variable

Source: own research based on literature and European Union (2021).

On the input side, they adopted eight indicators; on the output side, they adopted twelve. In selecting the individual indicators assigned to an input or output group, they were guided by the approach presented in the literature by other authors (Łącka, Brzezicki, 2021; Teirlinck, Spithoven, 2023; Teirlinck, Khoshnevis, 2022; Xu et al., 2019; 2020) and the nature of the indicator in focus. The authors, taking into account the approach presented by Bianchini *et al.* (2023), indicating the EU's increasing emphasis on the environmental problem, decided to consider the indicator "Air emissions in fine particulates (PM2.5) in Industry" as an undesirable output. The study by Lv *et al.* (2021) shows that RIS can be an effective influence in reducing atmospheric GHG emissions. It is worth noting that the literature (Łącka, Brzezicki, 2022) increasingly shows the consideration of environmental conditions when examining a region's innovation performance and its impact on SDG targets. It is all the more so as researchers are now paying attention to the dual changes that are taking place globally in terms of digital transformation and environmental protection (Bianchini et al., 2023). Authors who analyzed the efficiency of RIS considering undesirable outputs mostly included CO_2 or SO_2 emissions (Stergiou et al., 2024; Xu et al., 2019; 2020). However, only one pollution variable "Air emissions in fine particulates (PM2.5) in Industry" was available in the RISiE database at the regional level. Therefore, the authors of this study first determine that the variable is more relevant to decision makers in Europe than others related to environmental pollution. Secondly, the authors tried to preserve the original approach presented in RISiE. Accordingly, this variable was included in this study. It is worth noting that the EU pays special attention to innovation and pollution reduction, which reflected in the creation of the Eco-innovation Scoreboard (Łącka, Brzezicki, 2022; Hajdukiewicz, Pera, 2023). This study uses the GHG emissions productivity indicator as one of the indicators of the 'resource efficiency outcomes' area (European Commission, 2024). Since the data available in RISiE is characterised by low order-of-magnitude variation between variables, the authors decided, in line with the literature (Cooper et al., 2007), to use the assumption of constant returns to scale in the DEA model.

The data collected in RISiE allows the analysis of RIS at the NUTS-2 level over a more extended period. The authors assumed that this study will use data from 2014–2021. The adopted research period considers the EU cohesion policy period in 2014–2020 and the first year of the new period 2021–2027. It is worth noting that cohesion policy is one of the most important policies of the European Union aimed at reducing inequalities between the regions of the EU member states. In addition, the authors assumed that the analysis would cover the same NUTS-2 for the entire research period, i.e. 2014–2021.

The selection of surveyed units for the study was as follows. The starting point was the list of RIS units from 2014, with a total of 210, followed by the addition of data from the following years 2015–2021 and a check of the completeness of data in all indicators for each RIS. A unit cannot be included in the study by means of DEA if there is a missing numerical value. Therefore, they excluded from the study those units for which they could not obtain complete data for the entire period. Finally, they adopted 146 NUTS-2 units for the study (Table A2 in Appendix).

Results and discussion

Following the adopted research procedure, the first step was to estimate the efficiency of RIS. Table 3 presents descriptive statistics of the efficiency scores for each year of the study. The average efficiency scores were high throughout the period, above 0.900, while the variation of units measured by the standard deviation (st. dev.) was relatively small, ranging from 0.098 to 0.136. On the one hand, the observed results may indicate that RIS in Europe is highly efficient. In fact, the number of efficient units in our study is higher than one might have thought but this is due to reasons other than the DEA model itself. On the other hand, they revealed an intriguing relationship. The better the RIS unit, the more systematically it reports its results (no data gaps). It was somewhat confirmed by analysing the source data and the trends in data reporting for RISiE.

Table 3. Descriptive statistics of efficiency indicators

Specification	2014	2015	2016	2017	2018	2019	2020	2021
Min	0.377	0.393	0.386	0.207	0.194	0.288	0.292	0.571
Mean	0.959	0.957	0.962	0.957	0.964	0.945	0.955	0.963
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
St. dev.	0.123	0.126	0.119	0.134	0.125	0.136	0.129	0.098

Source: own elaboration.

An interesting trend was noted when dividing the NUTS-2 units into efficient and inefficient (Table 4). In 2015, the number of efficient RIS decreased by one unit compared to 2014. Then, from 2016 to 2018, their number was stable at 130 units. In 2019, there was a considerable reduction in the number of efficient NUTS-2 to 119 units. On the other hand, between 2020 and 2021, a constant number of 126 units could again be observed. It can, therefore, be concluded that, apart from 2019, there was relative stability in the number of efficient units. It is noteworthy that the highest number of inefficient units in the study period 2014–2021 was recorded in 2019. Not only was the average value of RIS efficiency in 2019 the lowest of the entire study period, even lower than the initial year 2014, but also the highest variation of RIS units studied was recorded in 2019 (st. dev. 0.136). The number of efficient RIS in the period 2014–2021 ranged between 82% and 89% of all surveyed units.

Research on RIS points out the significant role of universities, science, and research parks in creating effective networks in innovation processes (Theeranattapong et al., 2021). However, according to ongoing research presented in the literature, these actors do not always focus on applied solutions for industrial needs but rather on theoretical and scientific ones. Studies by Brzezicki and Prędki (2023) and Łącka and Brzezicki (2023) show that both research institutes and universities in Poland focus more on publishing scientific papers than on patents and practical implementations into the economy. In contrast, a comparative analysis by Dusdal *et al.* (2020) of German universities and research institutes shows that the latter generate more articles in science, technology, engineering and mathematics, medicine, and health. Furthermore, compared to universities, they publish these articles in journals with a higher Impact Factor.

Table 4. Number and share of efficient and inefficient NUTS-2 from 2014 to 2021

Year	N/%	Efficient	Inefficient	Total
2014	N	129	17	146
2015		128	18	146
2016		130	16	146
2017		130	16	146
2018		130	16	146
2019		119	27	146
2020		126	20	146
2021		126	20	146
2014	%	88.36	11.64	100.00
2015		87.67	12.33	100.00
2016		89.04	10.96	100.00
2017		89.04	10.96	100.00
2018		89.04	10.96	100.00
2019		81.51	18.49	100.00
2020		86.30	13.70	100.00
2021		86.30	13.70	100.00

Notes: N – number of NUTS-2 units.

Source: own elaboration.

The increase in the number and share of inefficient units in 2020–2021 compared to 2014–2018 may result from the impact of the COVID-19 pandemic on the economy of the EU and its regions. The pandemic shocked the global and EU economies and companies' innovation activities (Santos et al., 2021). On the one hand, the conditions for innovation processes deteriorated due to supply and demand shocks in specific sectors and regions. On the other hand, pandemic crises (health, social and economic) have led to spectacular growth in some industries and technologies and a significant acceleration of innovation processes. Nevertheless, some of the RIS in EU countries and other parts of the world could not achieve the same efficiency as in previous periods (Miranda Junior et al., 2022). The coronavirus pandemic provided the impetus to reflect on the functioning of innovation systems worldwide, e.g., in developing countries during and in the post-pandemic world (Singh, Joseph, 2024). Fig. 1 presents the spatial division of NUTS-2 into efficient and inefficient regions in the two extreme years of the study. The graphical depiction of the distribution of units shows that in 2014 and 2021 (apart from a few exceptions), there was no definite accumulation of inefficient units in one country or territorial area.

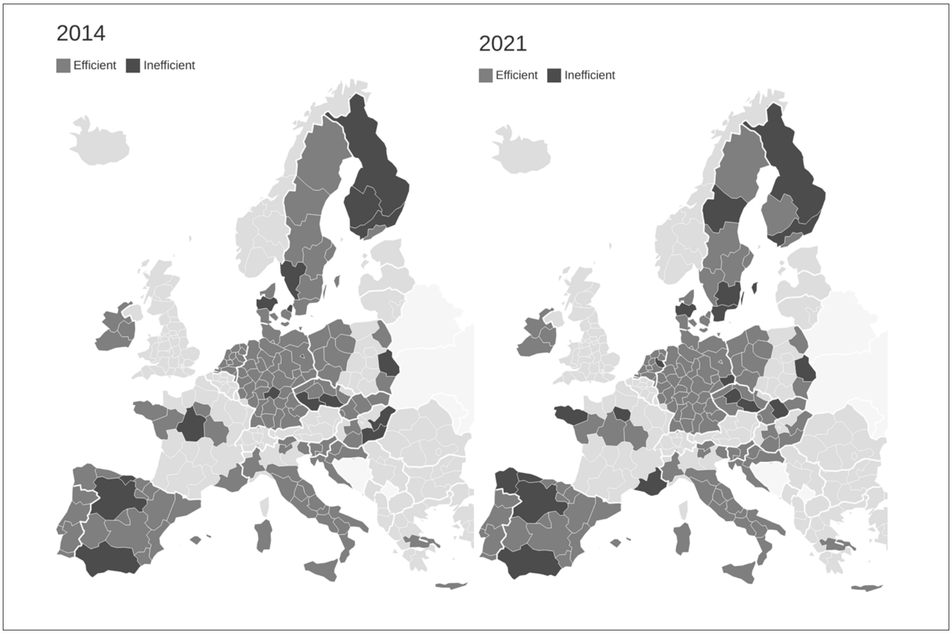

Fig. 1 Spatial division of NUTS-2 into efficient and inefficient in the two extreme years of the survey

Source: own elaboration.

The mentioned exceptions (at least 2 NUTS-2 inefficient units) concern Finland (2014, 2021), the Czech Republic (2014, 2021), Hungary (2014) and Spain (2014, 2021). Furthermore, it was noted that there are no significant differences between the two survey years for efficient and inefficient units. The changes in efficiency mainly concern single RIS. Notably, some units remained inefficient in the two years of the survey, while others either gained efficient status in 2021 or, on the contrary, became inefficient. For example, FI19 and SE23 were considered inefficient in 2014 and efficient in 2021. The reverse was true for, among others, SE21 and SE22, which were initially deemed efficient in 2014 but inefficient in 2021. The change in status did not apply to FI1D, FI1C, ES61, ES41 and PL81, among others, which were inefficient in the two extreme years of the study.

The following research used the Super-SBM model with undesirable outputs to perform a RIS innovation ranking. The results of ranking the ten most and least efficient NUTS-2 from 2014 to 2021 are presented in Table 5. The research did not reveal a straightforward leader who was the most efficient each year. However, the EL64 unit emerged as the leader in 2016, 2018, 2020 and 2021, and ITG2 in 2014–2015. Several units were noted to be among the ten most efficient RIS in different years. Although a single RIS has proved most effective in some years, not in all, so H2 has been positively verified. In contrast, the least efficient unit in 2014–2018 was HU32; in 2019–2020, it was PL81. The situation changed in 2021 when the FRH0 was ranked last. Unit PL81 is located in the area of Eastern Poland, which has long shown a lower level of development than the rest of the country. For many years, central, regional and local governments have been taking many pro-development and pro-innovation activities in this area of Poland. They aim to accelerate the region's development. Unfortunately, it still shows a certain distance concerning the other regions of Poland.

The authors decided that the results obtained with the Super-SBM model with undesirable outputs had compared with those obtained by RIS in RISiE. As it turned out, the results differed, and a negative correlation was obtained between them. It means that the better the RIS score in RISiE, the weaker the level of efficiency is achievable. The difference is due to the method used to estimate the efficiency in RISiE and the DEA method. In the case of RISiE, all variables are considered together – whether they relate to inputs or outputs of RIS functioning. In contrast, in the case of the present analysis using the DEA method, the authors distinguished between variables on inputs and outputs of RIS operation. When estimating efficiency, we focused on the level of outputs obtained. It should be noted here that when evaluating the performance of an entity, whatever it may be (company, institution, territorial unit, etc.), the outputs of its work are more important than the inputs devoted to producing outputs. It is not always the case that more significant inputs contribute to more significant outputs of an entity. Therefore, the authors agree with the findings presented by Teirlinck and Spithoven (2023), who point out that the evaluation scale in RISiE inadequately reflects differences in efficiency in transforming knowledge inputs into innovation outputs. Furthermore, the authors argue for the extension of RISiE to include an indicator estimating the level of efficiency of individual RIS – a point also highlighted by Teirlinck and Spithoven (2023) in their study.

Table 5. Ranking of the ten most and least efficient NUTS-2 from 2014 to 2021

	2014		2015		2016		2017		2018		2019		2020		2021	
No	U	Eff.	U	Eff.	U	Eff.	U	Eff.	U	Eff.	U	Eff.	U	Eff.	U	Eff.
1	ITG2	3.074	ITG2	3.011	EL64	3.498	CZ04	5.078	EL64	4.794	ITH1	1.774	EL64	2.642	EL64	2.729
2	EL43	2.143	EL64	2.038	ITG2	3.140	EL64	3.900	EL43	2.006	CZ04	1.760	ITH1	1.854	EL43	1.917
3	EL64	2.043	EL43	1.958	EL43	2.382	ITG2	2.256	DE22	1.701	EL43	1.678	PT15	1.723	PT15	1.793
4	CZ04	1.622	CZ04	1.644	ITG1	1.566	EL43	2.024	ES53	1.620	ES53	1.667	DEE0	1.608	SI03	1.727
5	ITG1	1.524	ITG1	1.544	ES53	1.543	DE22	1.791	ITH1	1.590	DEE0	1.453	EL43	1.569	ITH1	1.499
6	ITF6	1.508	ES53	1.455	CZ04	1.467	ITH1	1.696	ITG2	1.555	HR03	1.452	ES53	1.542	CZ04	1.346
7	DE93	1.430	ITH1	1.401	DE22	1.415	ITF5	1.600	CZ04	1.546	PT15	1.404	DE93	1.485	ITG2	1.327
8	ES53	1.401	ITF5	1.342	ITH1	1.379	ES53	1.542	ITF5	1.346	ITF2	1.379	ITG2	1.474	HR03	1.291
9	ITH1	1.381	FRC1	1.316	ITF5	1.318	PT15	1.470	DK05	1.331	ITG2	1.346	SI03	1.463	SI04	1.283
10	FRC1	1.356	DE22	1.305	DE93	1.291	ITF3	1.284	HR03	1.284	ES23	1.289	CZ04	1.385	ES62	1.276
137	FRB0	0.670	DK01	0.642	ES61	0.750	CZ02	0.698	FI19	0.776	SE33	0.656	SI04	0.690	ES11	0.698
138	CZ03	0.655	FI1C	0.638	FI1C	0.650	PT16	0.688	SE23	0.764	FI1D	0.638	FI1D	0.666	ES41	0.694
139	DK01	0.649	FRB0	0.632	DK01	0.636	FI1D	0.682	SI04	0.738	SI04	0.626	SE33	0.619	SE32	0.690
140	FI1C	0.629	FI1D	0.618	FRB0	0.622	FRH0	0.558	PT16	0.721	PL84	0.611	FRH0	0.615	FRL0	0.688
141	FI1D	0.606	HU23	0.547	HU23	0.599	CZ06	0.555	FI1D	0.686	SE12	0.556	SE12	0.590	DED2	0.666
142	ES13	0.566	CZ06	0.523	ES13	0.565	FRB0	0.528	SE33	0.473	PL63	0.541	FRB0	0.561	PL81	0.662
143	CZ06	0.529	SE33	0.522	CZ06	0.544	PL81	0.499	FRB0	0.450	FRB0	0.507	PL63	0.518	CZ02	0.647
144	HU33	0.438	HU33	0.476	HU33	0.477	SE33	0.404	PL81	0.430	HU33	0.480	HU33	0.438	ES12	0.623
145	PL81	0.418	PL81	0.427	SE33	0.429	HU33	0.378	HU33	0.358	HU32	0.344	HU32	0.391	CZ06	0.613
146	HU32	0.377	HU32	0.393	HU32	0.386	HU32	0.207	HU32	0.194	PL81	0.288	PL81	0.292	FRH0	0.571

Notes: U – DMU, Eff. – efficiency, No – Rank position.

Source: own elaboration.

Since the average values of the efficiency scores in the SBM model with undesirable outputs in each year were high (above 94%), it was not possible to divide NUTS-2 into four groups according to the methodology used in RISiE (i.e. Innovation Leaders – 125% of the average value, Strong Innovators – between 100% and 125% of the average, Moderate Innovators – between 70% and 100% of the average and Modest Innovators – below 70% of the average). Only applying the Super-SBM model with undesirable outputs allowed the authors to divide the NUTS-2 surveyed into four groups. The results are presented in Fig. 2. The difference between Fig. 1 and Fig. 2 needs to be explained at this point. The application of the SBM model with super-efficiency and undesirable outputs allowed the RIS units to be divided in more detail. The efficient units in Fig. 1 were divided into two groups, i.e. Innovation Leaders, and were partly allocated to the Strong Innovators group when their efficiency values were close to 125% of the average for the whole research sample (at least above 107% of the average). The inefficient units in Fig. 1 were also divided into two groups, i.e. Moderate Innovators and Modest Innovators.

The first point worth noting when looking at Fig. 2 is that the RIS is significantly less differentiated in 2021 than in 2014. It is likely that we may be dealing with a convergence effect of innovation in European regions.

Fig. 2 Spatial division into NUTS-2 innovation performance groups in the two extreme years of the survey

Notes: Group 1 – Innovation Leaders, Group 2 – Strong Innovators, Group 3 – Moderate Innovators, Group 4 – Modest Innovators.

Source: own elaboration.

Comparison of data for 2021 with data from 2014 showed that some entities, such as Italian regions (e.g. Sicily, Sardinia), not only improved their situation compared to 2014 (group 4), but also ranked up to group 2. A more spectacular change can be seen in the Czech region located in the north-west of the country. It improved its efficiency so much that, in 2014, it was in group 4 and was promoted to group 1 in 2021. However, not every region retained its competitive advantage in terms of innovation, because, for example, the Lublin Voivodeship (in Poland) in 2014 was ranked at the top of the efficiency ranking, but in 2021, unfortunately, it was only in group 3. A comparison of the number of efficiency groups in 2014 versus 2021 shows a reduction of one.

Table 6 shows the number of RIS in each efficiency group. The highest number of units is in group 2, followed by group 3.

Table 6. Number and share of individual NUTS-2 efficiency groups 2014–2021

		Efficiency groups				
Year	N/%	1	2	3	4	Total
2014	N	10	93	39	4	146
2015		8	104	29	5	146
2016		8	82	53	3	146
2017		9	68	64	5	146
2018		7	90	44	5	146
2019		9	110	23	4	146
2020		12	107	23	4	146
2021		7	112	27	0	146
2014	%	6.85	63.70	26.71	2.74	100.00
2015		5.48	71.23	19.86	3.42	100.00
2016		5.48	56.16	36.30	2.05	100.00
2017		6.16	46.58	43.84	3.42	100.00
2018		4.79	61.64	30.14	3.42	100.00
2019		6.16	75.34	15.75	2.74	100.00
2020		8.22	73.29	15.75	2.74	100.00
2021		4.79	76.71	18.49	0.00	100.00

Notes: 1 – Innovation Leaders, 2 – Strong Innovators, 3 – Moderate Innovators, 4 – Modest Innovators, N – number of regions

Source: own elaboration.

When comparing the efficiency results in the following years, it is worth noting that the most remarkable change (shifts between groups 2 and 3) occurred in these groups. In the case of group 2 (Strong Innovators), it was observed that there was a significant decrease in efficiency in two periods (2016 and 2017) compared to the previous year. In the other periods, there was an upward trend. In contrast, the fewest units were recorded in group 4 (Modest Innovators) and group 1 (Innovation Leaders). Interestingly, in 2017, the number of units in group 2 and group 3 were similar, at 68 and 64, respectively.

In addition, similar units were observed in these groups (1 and 4) (the most negligible variation between years in the group). When comparing year-on-year performance results, the authors noted that the most significant variability occurred in group 3. According to Xu *et al*. (2023b), economic development, investment in human capital and regional openness can increase innovation efficiency in most EU regions. In contrast, industrial structure, urbanisation, and infrastructure hinder improving European innovation efficiency. The results of our study partially coincide with those of Stergiou *et al*. (2024), who indicated that improving the efficiency of knowledge generation results in a reduction of greenhouse gas emissions. The shifts between efficiency groups in our study are due, on the one hand, to more efficient generation of good RIS outputs and, on the other, to attention to reducing undesirable outputs in terms of environmental pollution.

Conclusions

The appropriately designed research process and the research results obtained through it made it possible to answer the defined research questions. The results of the first research stage allowed the first research question (Q1) to be answered. The authors' research into the efficiency of regional innovation systems in Europe has shown as between 82% and 89% of NUTS-2 were efficient throughout the study period. Their share was the highest between 2015 and 2018.

The second research stage allowed the second (Q2) and third (Q3) research questions to be answered. The research showed that between 2014 and 2021, there was no clear leader with the highest efficiency each year. Based on the Super-SBM model with undesirable outputs, the authors prepared a ranking of the ten most and ten least efficient units in the period studied. It shows that no single region can be identified as the efficiency leader in innovation. It was possible to establish that leadership in this respect over the most prolonged period (2016, 2018, 2020 and 2021) was achieved by the EL64 unit. Among the most inefficient NUTS-2 units, HU32 showed this status for the longest time, between 2014 and 2020.

The research showed that European regions belonged to different innovation groups, with the Innovation Leaders group being the least numerous. The Strong Innovators and Moderate Innovators groups (the most numerous) had the most prominent changes and shifts between groups. The authors noted that in 2021, no individuals were described as Modest Innovators. This indicates, on the one hand, that the innovation of the RIS has improved and, on the other hand, that the narrow classification of groups according to the EIS methodology results in a reduction in the number of groups in the long term.

Although this study filled a gap in the literature, it also has limitations. Firstly, the study excluded NUTS-2, for which it was impossible to obtain complete data for the entire study period, i.e. 2014–2021. Future studies should cover all NUTS-2 included in the different editions of RISiE. In order to do this, DEA models that consider uncertain data (e.g. fuzzy data, interval data) should be used. Secondly, the authors only analysed the past period based on historical data. Therefore, historical analysis can be considered in the future, and a prediction of future performance can be made. Thirdly, the study did not consider external factors affecting the obtained RIS efficiency results. It should be done by using methods (e.g. CNLS with contextual variables) and procedures (e.g. two-stage analysis) that take so-called environmental variables into account in the study when estimating efficiency. Fourthly, it is necessary to analyse changes in productivity between the years of the study. Another interesting research direction is the analysis of urban innovation and subsystems within RIS, e.g. sectoral innovation systems. It would build on research already undertaken in this area (Cano et al., 2023).

Recommendations for RIS policy on the EIS-RISiE tool

The authors' analyses of quantitative efficiency (based on RISiE database data) indicate that many RIS in the European Union are characterised by efficiency. However, this presented approach using RISiE data on inputs and outputs has many cognitive limitations. This is due to the numerous shortcomings of the RISiE. Firstly, this report lacks indicators capturing the quality of interactions between individual institutions, actors or people, or even data on cooperation between closer and further RIS (network effects), which can synergise to increase the efficiency and effectiveness of a particular RIS. Secondly, considering the sustainable development promoted in the EU, RISiE lacks more variables showing the environmental impact of innovations (only one variable is related to air pollution of fine dust from industry). Thirdly, among the RISiE data, no variables show the particular specialisation of the RIS or the adopted strategy for innovation development in the region. Consequently, RIS is assessed through the prism of the whole research sample rather than a subsample, which would have allowed the researchers to obtain more detailed analysis results. It is worth noting that in recent years, RIS efficiency issues have gained importance in the context of the development of intelligent specialisations that will provide the region with long-term development and competitive advantage (Czyżewska-Misztal, Golejewska, 2016; Lopes et al., 2020). The drive to implement the proposed concepts in specific territories stems from the search by national and regional authorities for effective mechanisms for creating and diffusing innovation. The authors noted that some of the recommendations are gradually being implemented by the EU, albeit in a different way to RISiE. At the end of 2024, 148 regions in Europe have been awarded the title of Regional Innovation Valleys (RIV). The RIV initiative aims to create interconnected regional innovation valleys across the EU, by leveraging strategic areas of regional strength and smart specialisations (European Innovation Council and SMEs Executive Agency, 2023). Fourthly, RISiE lacks data at a lower level of aggregation for cities. It is, therefore, impossible to determine the strength of the impact of urban agglomerations on the efficiency of a given RIS, although the literature, using selected EU RIS as an example, indicates that metropolitan areas significantly influence innovation systems at a higher structural level (Fischer et al., 2001). Fifthly, RISiE does not provide information on the number of R&D institutions and innovation firms in an RIS. Their number and structure affect a given RIS's efficiency. The data in this respect would allow these units' economies of scale to be considered. Sixthly, there is no data on ICT in RISiE, and the dynamic development of these technologies can currently be seen. They are also an essential part of the network of relationships in innovation processes.

These arguments point to certain shortcomings of the RISiE methodology in a rapidly changing socio-economic environment and the increasing number of challenges facing RIS. In the context of the EU, it is worth highlighting actions the Community took, such as, among other things, the earmarking of EU funds for R&D activities and the promotion of human capital flows through Erasmus+ programmes. The information on this would make it possible to check the impact of the "EU effect" on individual RIS. Currently, there is a lack of such data in RISiE. The authors therefore recommend expanding the set of information collected to assess innovation activity in regional innovation systems in EU countries.

RISiE reports only include "hard" data characterising the institutional and formalised innovation system. They do not contain "soft" data, which could at least roughly show the "positive innovation climate" in the environment of innovation processes and the openness of society to the transfer of formal and tacit knowledge in interpersonal interactions. Introducing this type of data into the research on regional innovation and the operation of RIS would make it possible to assess the social potential for innovation, the barriers to knowledge and technology transfer and the areas of necessary support.

Attachments

Table A1. List of acronyms

Acronyms	Clarify
BCC	Banker, Charnes & Cooper model DEA
CCR	Charnes, Cooper & Rhodes model DEA
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
EIS	European Innovation Scoreboard
EU	European Union
GHG	Greenhouse Gas Emission
NIS	National Innovation System
NUTS	EU established in 2003 a common classification of territorial units for statistics called NUTS at three structural levels (hierarchical system). NUTS-2 is regions
R&D	Research and Development
RIS	Regional Innovation Systems
RISiE	Regional Innovation Scoreboard in Europe
SBM	Slacks Based Measure model DEA
Super-SBM	Slacks Based Measure model DEA with super efficiency

Table A2. Overview of NUTS-2 included in the RIS study

No.	Country	Code	No.	Country	Code	No.	Country	Code	No.	Country	Code	No.	Country	Code
1	Belgium	BE10	31	Germany	DE73	61	Spain	ES23	91	Italy	ITF1	121	Poland	PL81
2	Czechia	CZ01	32	Germany	DE80	62	Spain	ES24	92	Italy	ITF2	122	Poland	PL82
3	Czechia	CZ02	33	Germany	DE91	63	Spain	ES30	93	Italy	ITF3	123	Poland	PL84
4	Czechia	CZ03	34	Germany	DE92	64	Spain	ES41	94	Italy	ITF4	124	Portugal	PT11
5	Czechia	CZ04	35	Germany	DE93	65	Spain	ES42	95	Italy	ITF5	125	Portugal	PT15
6	Czechia	CZ05	36	Germany	DE94	66	Spain	ES43	96	Italy	ITF6	126	Portugal	PT16
7	Czechia	CZ06	37	Germany	DEA1	67	Spain	ES51	97	Italy	ITG1	127	Portugal	PT17
8	Czechia	CZ07	38	Germany	DEA2	68	Spain	ES52	98	Italy	ITG2	128	Portugal	PT18
9	Denmark	DK01	39	Germany	DEA3	69	Spain	ES53	99	Hungary	HU21	129	Slovenia	SI03
10	Denmark	DK02	40	Germany	DEA4	70	Spain	ES61	100	Hungary	HU23	130	Slovenia	SI04
11	Denmark	DK03	41	Germany	DEA5	71	Spain	ES62	101	Hungary	HU32	131	Slovakia	SK01
12	Denmark	DK04	42	Germany	DEB1	72	France	FR10	102	Hungary	HU33	132	Slovakia	SK02
13	Denmark	DK05	43	Germany	DEB2	73	France	FRB0	103	Netherlands	NL11	133	Slovakia	SK03
14	Germany	DE11	44	Germany	DEB3	74	France	FRC1	104	Netherlands	NL12	134	Slovakia	SK04
15	Germany	DE12	45	Germany	DED4	75	France	FRG0	105	Netherlands	NL13	135	Finland	FI19
16	Germany	DE13	46	Germany	DED2	76	France	FRH0	106	Netherlands	NL21	136	Finland	FI1B
17	Germany	DE14	47	Germany	DED5	77	France	FRL0	107	Netherlands	NL22	137	Finland	FI1C
18	Germany	DE21	48	Germany	DEE0	78	Croatia	HR02	108	Netherlands	NL23	138	Finland	FI1D
19	Germany	DE22	49	Germany	DEF0	79	Croatia	HR03	109	Netherlands	NL31	139	Sweden	SE11
20	Germany	DE23	50	Germany	DEG0	80	Croatia	HR05	110	Netherlands	NL32	140	Sweden	SE12
21	Germany	DE24	51	Ireland	IE04	81	Croatia	HR06	111	Netherlands	NL33	141	Sweden	SE21
22	Germany	DE25	52	Ireland	IE05	82	Italy	ITC1	112	Netherlands	NL34	142	Sweden	SE22
23	Germany	DE26	53	Ireland	IE06	83	Italy	ITH1	113	Netherlands	NL41	143	Sweden	SE23
24	Germany	DE27	54	Greece	EL43	84	Italy	ITH2	114	Netherlands	NL42	144	Sweden	SE31
25	Germany	DE30	55	Greece	EL64	85	Italy	ITH4	115	Poland	PL41	145	Sweden	SE32
26	Germany	DE40	56	Spain	ES11	86	Italy	ITH5	116	Poland	PL42	146	Sweden	SE33
27	Germany	DE50	57	Spain	ES12	87	Italy	ITI1	117	Poland	PL43			
28	Germany	DE60	58	Spain	ES13	88	Italy	ITI2	118	Poland	PL51			
29	Germany	DE71	59	Spain	ES21	89	Italy	ITI3	119	Poland	PL61			
30	Germany	DE72	60	Spain	ES22	90	Italy	ITI4	120	Poland	PL63			

Source: own elaboration based on European Commission (2022a).

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