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Efficiency Determinants of Regional Innovation Systems in Polish Subregions*

Determinanty efektywności regionalnych systemów innowacyjnych w polskich podregionach

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Abstract

In the current knowledge-based economy paradigm, it is innovativeness that may enable lagging regions to be as competitive as more developed regions. The innovation and efficiency of regional innovation systems (RISs) are crucial for enhancing economic development. Using data envelopment analysis (DEA) with environmental factors, we conducted an assessment of the efficiency of RISs in Polish subregions. On this basis, a list was drawn up of efficient subregions with strong innovation as well as efficient regions with weak innovation. The results confirm that, in most cases, Polish subregions are not using their full potential. While estimating the panel model, RIS features that influenced efficiency were identified, and the positive impact of the innovative milieu, spatial proximity and the share of industry in value added were confirmed. The negative impact of unemployment and factors reflecting the low level of social capital were identified. The obtained results may be the basis for formulating an appropriate innovation policy at the regional level, especially in Central and Eastern European countries. We suggest that the use of the identified patterns, in combination with the individual characteristics of particular regions, may contribute to an improvement in both technological effectiveness and productivity, particularly in weaker regions.

Keywords:
efficiency, DEA, CEE countries, regional innovation system, panel model

JEL classification codes:
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Streszczenie

W obecnym paradygmacie gospodarki opartej na wiedzy to właśnie innowacyjność może sprawić, że regiony zapóźnione w rozwoju będą tak samo konkurencyjne jak regiony bardziej rozwinięte. Czynniki innowacyjne i efektywność regionalnych systemów innowacji (RIS) są kluczowe dla wzmocnienia rozwoju gospodarczego. Wykorzystując analizę obwiedni danych (DEA) z czynnikami środowiskowymi, przeprowadzono ocenę efektywności RIS w polskich podregionach. Na tej podstawie stworzono listę efektywnych podregionów o silnej innowacyjności oraz efektywnych regionów o słabej innowacyjności. Uzyskane wyniki potwierdzają, że w większości przypadków polskie podregiony nie wykorzystują w pełni swojego potencjału. Estymując model panelowy, zidentyfikowano cechy RIS wpływające na efektywność, potwierdzono pozytywny wpływ środowiska innowacyjnego, bliskości przestrzennej oraz udziału przemysłu w wartości dodanej. Zidentyfikowano

Słowa kluczowe:
efektywność, DEA, kraje EŚW, regionalne systemy innowacyjne, model panelowy

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negatywny wpływ bezrobocia oraz czynników świadczących o niskim poziomie kapitału społecznego. Uzyskane wyniki mogą stanowić podstawę do formułowania odpowiedniej polityki wspierającej innowacje na poziomie regionalnym, zwłaszcza w krajach Europy Środkowo-Wschodniej. Wykorzystanie zidentyfikowanych wzorców w połączeniu z indywidualnymi cechami poszczególnych regionów może przyczynić się do poprawy zarówno efektywności technologicznej, jak i produktywności – szczególnie w regionach słabszych.

Introduction

In an era of globalisation and economic integration, one of the most important problems is to identify patterns and mechanisms that can enable lagging regions to catch up with the most developed ones in terms of the level of competitiveness. We observe that China, using a centrally planned economy, has achieved enormous success, becoming the world's second-largest economy. It would seem that the key to success in this case was state interventionism, and perhaps some political forces would be tempted to choose such a path for economic policy also in European countries, especially those in Central and Eastern Europe. Some advocated this kind of approach in the face of the crisis caused by the COVID-19 pandemic. However, there are at least two points to note. First, in Far Eastern countries there is a completely different culture based on the philosophy of Confucius, in which obedience to authority and faith in the wisdom of political leaders are deeply rooted. Second, China's success is to a large extent the result of assigning a key role to innovation, both homegrown and that imitating Western solutions. Hence, in the modern economy, innovation is considered to be one of the most important factors of competitiveness at both the national and regional levels.

The European Commission recognised the relationship between regional development and innovation in its Europe 2020 Strategy [**Eurostat, 2019**]. The introduction of Smart Specialisation Strategies aimed to ensure that all EU regions would be able to fully exploit their potential and succeed with an innovation-based industrial transition [**European Commission, 2018**]. In view of that, particular support should be given to the absorption of innovation in less developed regions and more traditional industries. However, according to **Barca** [**2009**], in order to achieve the best growth effects, regional economic policy should be adapted to the place at which the intervention is directed (the place-based policy). The spatially conditioned natural and institutional resources of a region should be taken into account, in addition to individual preferences and experiences (knowledge) as well as material and non-material spatial (interregional) connections. No further development can be achieved without the region's own innovations. Moreover, they can help avoid the middle-income trap and the so-called glass ceiling of development.

Most Central and Eastern European countries including Poland are classified as innovation followers, which means economies that invest in existing technologies rather than develop genuine inventions [**Brandt, 2018**]. Although these countries have undergone a rapid transformation in the last 30 years, building inclusive economic and political institutions, improving the quality of infrastructure and education, and strengthening local entrepreneurship, the productivity and income gap in relation to the EU average is still about 25%–30% [**Kruczkowska et al., 2017**]. According to the European Bank for Reconstruction and Development [**EBRD, 2019**], "before the 2008 global financial crisis, it was fashionable to call the Central and Eastern European economies 'tiger economies.' [...] Today, it may be time to talk about the 'phoenix economies.' They have risen again. In order to fly, they need nothing more than innovation."

Many economists are rediscovering the importance of regional scale and regional resources in stimulating the innovative capacity and competitiveness of firms and regions. However, firm-specific competencies and learning processes will not lead to a regional competitive advantage if they are not based on local capabilities, such as specialised resources, skills, institutions and shared social and cultural values [**Barca, 2009**]. Therefore innovative factors and the efficiency of the Regional Innovation System (which is defined in the next section) are crucial for enhancing economic development [**De Bruijn, Lagendijk, 2005**].

The aim of this analysis was to evaluate the efficiency of the Regional Innovation System (RIS) in Polish sub-regions between 2005 and 2016. The identification of the system's efficiency and its determinants is one of the most important elements allowing for an evaluation of a RIS. It should be clarified, however, that productivity, measured for example by the number of innovations introduced in a subregion in a given year, is not the same as efficiency since the latter compares both the effects and the inputs. This means that one RIS may be more productive and at the same time less efficient than another, which is less productive. A review of the literature shows significant limitations in empirical studies on the efficiency evaluation of innovation systems at the subregional level. The purpose of this paper is to fill this gap. The study was conducted to identify weak RISs, assessed as efficient but not highly productive, and strong RISs, which are efficient and at the same time highly innovative. A research hypothesis of differential influence of regional environment elements on the technological efficiency of firms was adopted. By providing information about the impact of regional factors on the level of corporate efficiency the paper contributes to the development of innovation policies in general. It makes it possible to propose policy implications that take into account a broad spectrum of regional innovation drivers.

Regional Innovation System concept

Traditional innovation analyses focus on linear models of innovation. However, it is the interaction of several factors and the synergy between them that determines the final innovation outcome [**Carayannis, Goletsis, Grigoroudis, 2015**; **Wojnicka-Sycz, 2020**]. The concept of the RIS, which emerged in the 1990 s, proves that the regional dimension is crucial for innovation systems [**Asheim, Gertler, 2009**; **Cooke, Boekholt, Tödtling, 1999**; **Doloreux, Parto, 2005**; **Sternberg, 2007**]. According to many studies related to innovation systems, regions are considered to be key to the effective performance of innovation systems for three reasons: first, they differ in their industrial specialisation and innovation position [**Paci, Usai, 2000**]; second, knowledge spillovers are usually geographically bounded [**Asheim, Coenen, 2005**; **Stejskal, Hajek, 2015**]; and third, tacit knowledge is important for innovation processes [**Gertler, 2003**; **Howells, 2002**; **Stejskal, Kuvíková, Meričková, 2018**].

The literature lacks a universally accepted definition of RIS [**Asheim, Isaksen, 2002**; **Cooke, 2001**; **Doloreux, Parto, 2005**; **De Laurentis, 2006**]. According to one definition that has gained considerable acceptance, a region can be referred to as a RIS if it is a collection of interplaying private and public interests, formal institutions and other organisations which operate in accordance with their organisational and functional agreements and relationships, encouraging the generation, use and diffusion of knowledge [**Doloreux, Parto, 2005**]. A holistic approach to the term was introduced by **Edquist** [**2000**], who described it as a system that contains all the important determinants of innovation.

Also, there is no universal approach in the classification of RIS components [**Carlsson, Stankiewicz, 1991**; **Fischer, 2001**]. A system consists of components, their relations and functions. The important components of each system are activities resulting from geographical, cultural and finally e-proximity, trust and willingness to cooperate. Such a system, also understood as an ecosystem, should include all entities indicated in the five-pointed helix concept: enterprises, science, administration, society, and the natural environment [**Carayannis et al., 2018**]. According to **Wojnicka-Sycz** [**2020**], it should actually be a six-pointed helix taking into account the block of intermediary institutions, which is important in innovative systems. Finally, the proper functioning of the system requires communication links between subjects. To conclude, a RIS may be described as a system fixed into the socioeconomic regional environment involving entities from various sectors. Generally, RISs are increasingly considered as a factor of economic development, a type of regional policy [**Philip Cooke et al., 1999**; **Edquist, 2014**], and are defined as systems which stimulate the innovative capacities of local firms and strengthen the growth potential and competitiveness of a region [**Braczyk, Cooke, Heidenreich, 1998**; **Golejewska, 2019**].

There is no single universal method of analysis and evaluation for a RIS, but a review of selected methods is presented by Stejskal et al. [2018]. These include participatory evaluation [Diez, Esteban, 2000], network analysis [Krätke, 2002], cluster analysis [Roelandt, Hertog, 1999], DEA, regression models, case studies, comparative studies, and qualitative content analysis [Hsieh, Shannon, 2005]. The research problems posed in the literature essentially concern three areas: the structure, dynamics and efficiency of innovation systems.

Regional Innovation Systems show significant differences in terms of quality and efficiency [Doloreux, Dionne, 2008; Fernández-Serrano, Martínez-Román, Romero, 2019]. There are many analyses of the innovativeness of Polish regions (for a review see Golejewska [2019]), but only a few are strictly related to RISs, and efficiency studies of RISs in Poland are rare. Golejewska [2019] identifies regions that can be described as strong, equipped with innovative potential and efficient at the same time (Mazowieckie, Śląskie, Dolnośląskie and Małopolskie), despite the fact that regional innovation systems in Poland are considered to be fragmented and in an initial formative phase. The results of analysis carried out by Świadek [2011] confirm the significant impact of interactions with the environment on RISs. The innovation activity of industrial systems increases as the number of inter-industrial relationships grows. According to Nowakowska [2011], RISs in Poland either do not exist or are underdeveloped, in particular in organisational and institutional terms. Many regional projects undertaken to build innovation capacity are characterised by a high degree of individualism, and there is a lack of local leaders to initiate actions in the systems. In many cases, regional authorities have ceded this role to other institutions that are not very effective in building the region's innovative capacity [Nowakowska, 2011]. Meanwhile, Kondratiuk-Nierodzińska [2013] investigates the impact of the efficiency of regional systems on the competitiveness of Polish provinces. The author identifies two groups of provinces, one with high efficiency and a low level of competitiveness, and the other with low efficiency and a high level of competitiveness.

A review of empirical research confirmed the use of different methods of RIS evaluation in Poland, and comparative analyses are rather scarce. The few interregional comparisons include a study by the Polish Agency for Enterprise Development that aims to assess the impact of regional innovation policy on the creation and strengthening of the RIS [Plawgo et al., 2013]. Their authors use both a linear and a functional approach. While the first approach is focused on input and output indicators (e.g. Regional Innovation Scoreboard), in the more dynamic functional approach the emphasis is placed on the functions of the system, i.e. the creation of knowledge, absorption capacity, the role of local authorities, diffusion, demand, agglomeration effects, expenditure on R&D activities and regional accessibility [Hajek, Henriques, Hajkova, 2014]. There is a lack of comprehensive analyses covering the longer-term horizon that would allow for identification of development paths of individual systems, and one of the reasons for this is the quality of the available regional data.

The evaluation of efficiency, which is the purpose of this paper, is a comprehensive task, as it involves the evaluation of all factors, each individually and the system as a whole [Markard, Truffer, 2008]. The choice of efficiency measures depends on the level of analysis applied and the degree of maturity of the system [Carlsson et al., 2002; Golejewska, 2019].

RIS efficiency and its measurement

In the literature, it is often stressed that an efficient RIS is an important factor for regional innovativeness diversity. However, there is still limited knowledge of the real determinants of RIS efficiency, and the way in which RIS quality is measured is also ambiguous [Fritsch, Slavtchev, 2006]. The results of empirical analyses are largely based on case studies, and in the less numerous comparative studies the most commonly used concept is technological efficiency [Buesa et al., 2007; Dzemydaitë, Dzemyda, Galinienë, 2016; Fritsch, Slavtchev, 2006]. A system can be considered technologically efficient if it provides the maximum innovative result/product from a given amount of innovative input. The application of the concept of technological efficiency in the innovation process may be problematic for several reasons. First, innovation processes are stochastic in nature and their results are not precisely known. Second, due to the unique and individual nature of each innovation, the best and therefore appropriate way to achieve these results is also unknown. Even if the expected result was achieved by a particular procedure, this does not mean that the same procedure will be appropriate in other cases. Therefore, due to the variety of procedures and results, innovation processes are not comparable. However, inventions and innovations can be measured even if each of them is unique. To measure the efficiency of a RIS, the input-output relation may be used. Systems may transform their inputs into innovative outputs more or less efficiently, but the reasons for high RIS efficiency measured as the input-output ratio may be different. Properly managed innovation processes can result from making the right decisions at the right time, and other factors influencing the efficiency of a RIS are related to the regional and sectoral environment of the innovative entity [**Fritsch, 2004**].

Efficiency may refer to a single company, a sector, a region or an economy as a whole. Commonly used measurement methods are based on a single indicator as well as parametric and non-parametric approaches. The indicator analysis may be based on numerous indicators, the most important indicators or synthetic measures (*Regional Innovation Scoreboard*). However, there is still no universally applied input-output indicator system of innovation measurement in the literature [**Dziallas, Blind, 2019**]. Parametric methods require the adoption of assumptions concerning the form of the production function, which determines the relationship between the inputs and outputs. In practice, however, the observation of all possible combinations of inputs and outputs may not be possible, and therefore it is not possible to determine the mathematical form of the production function for an entity or a system [**Ćwiąkała-Małys, Nowak, 2009**]. Parametric methods assume the need to know the detailed process of generating effects, i.e. the production function in the broad sense, while non-parametric methods compare outputs with inputs without going into the production process itself. Efficiency assessments based on production functions are often fragmented in nature, taking into account only part of the efficiency category [**Szymańska, 2010**]. Non-parametric methods do not require knowledge of the functional relationship between inputs and outputs and are characterised by greater flexibility, as they are applied to models whose structure is not set up a priori, but is adapted to the data. In order to assess the effectiveness of RISs in empirical research, two methods are primarily used with various modifications: a parametric method – stochastic border analysis (SFA); [**Coelli et al., 2005**; **Kumbhakar, Lovell, 2000**]; and a non-parametric method – data envelopment analysis (DEA); [**Charnes, Cooper, Rhodes, 1978**]. In the case of the emergence of innovations, it is difficult to make assumptions about certain common parameters and the shape of the production function, and for this reason non-parametric methods are predominantly used.

The precursors of the DEA method were **Farrell** [**1957**], **Färe and Lovell** [**1978**], **Charnes, Cooper and Rhodes** [**1978**] and **Banker, Charnes and Cooper** [**1984**]. In this approach, efficiency in the sense of Pareto-Koopmans is analysed. It means that a producer works efficiently when, at certain levels of inputs, they cannot increase the production of one good without reducing the production of another, or, assuming that the results of production remain constant, they cannot reduce the consumption of one input without increasing the consumption of another input [**Domagała, 2007**; **Kumbhakar, Lovell, 2000**]. By applying this concept of efficiency, a RIS can be considered efficient if the growth of the variable interpreted as output requires an increase in the value of at least one of the variables considered as input – or, on the other hand, when reducing any of the inputs requires an increase in at least one of the remaining inputs or a decrease in the variable representing the result. **Mandl et al.** [**2008**] state that low rates of technical efficiency obtained by a given unit do not necessarily mean that it operates in an ineffective manner, but may reflect the influence of other factors that lead to a reduction in efficiency. These other factors are referred to as environmental variables [**Simar, Wilson, 2007**] and are not included in the inputs and outputs in the estimates of DEA indicators. These can be geographic, legal or economic conditions, which affect outputs or inputs and which cannot be controlled directly by the unit. The problem should be addressed in particular when assessing the efficiency of a RIS and the importance of its features for the level of inefficiency.

When applying the DEA method it is important to be cautious and aware of its limitations. The production-possibility frontier common for a group of units is determined, which reflects the maximum achievable effect at given levels of inputs. The units on the frontier are considered efficient, whereas the distance from this frontier to the other units indicates their degree of inefficiency. In other words, the ratio of the outputs obtained by a given unit and the inputs invested is compared to those achieved by the best units in the analysed set. This means that the efficiency determined in this way is a relative measure. The technique that enables the determination of the production-possibility frontier is quotient programming reduced to linear programming, in which we maximise a criterion function defined as the quotient of the weighted sum of outputs and the weighted sum of inputs [Charnes et al., 1978: 431]. Assuming that a common production-possibility frontier is determined, the group of units should be relatively homogeneous. It is assumed that they pursue the same goal and operate under the same external conditions. Moreover, the factors that characterise their activities are the same and differ only in the intensity of their application.

As previously mentioned, the advantage of the DEA method is its non-parametric character, i.e. no specific shape of the production function is assumed to reflect the technological process of innovation, and no specific distribution of efficiency measures. On the other hand, it should be remembered that this approach is sensitive to possible errors in measuring the variables used and unusual or outlier observations [Biorn et al., 2002]. Also, changes in the number of units in the group causes significant differences in the results, as it is based on determining the relative efficiency [Kozuń-Cieślak, 2012]. Moreover, a certain drawback of the efficiency estimates based on the DEA method is the inability to verify their quality with the use of traditional statistical measures. Therefore, bootstrapping methods are used to verify the quality of performance assessments.

The results of the simulation performed by Banker and Natarajan [2008] show that in the efficiency analysis of Decision Making Units, the DEA procedures prove to be more effective than the parametric methods. In addition, they are better adjusted to multiple outputs and non-linearity. Regions use their resources as efficiently as possible in order to achieve the objectives set by law, policy and social expectations, as they are all governed by elected regional authorities. These features make it possible to treat different regions as homogeneous, which enables their comparison using DEA [Żółtaszek, Olejnik, 2017]. Research by authors such as those listed below can be used as examples of regional analyses: Lafarga and Balderrama [2015] for Mexico, Buesa et al. [2007] for Spain, Zabala-Iturriagagoitia et al. [2007] and Żółtaszek and Olejnik [2017] for Europe, Dzemydaitė, Dzemyda and Galinienė [2016] for Central and Eastern Europe, and Chen and Guan [2012] for China. For Polish regions, DEA was implemented in the analysis of the innovative efficiency of industrial enterprises by Masternak-Janus and Rybaczewska-Błażejowska [2016] and, in combination with factor analysis, in the assessment of the technological performance of NUTS2 by Golejewska [2019].

Methods

Taking into account the specific features of Regional Innovation Systems, the aim of which is not to minimise inputs, but to achieve as many innovations as possible with the resources at hand, the appropriate orientation for the DEA is output orientation. Another issue that needs to be resolved is the returns to scale assumption. Originally, the DEA method proposed by Charnes, Cooper and Rhodes [1978] adopted a constant returns to scale assumption (DEA-CRS), while the modified models of Banker, Charnes and Cooper [1984] assumed variable scale effects (DEA-VRS). When returns to scale are not constant, it is also possible to check whether we are dealing with non-increasing returns (NIRS) or with decreasing returns to scale (DRS). According to the theory of microeconomics, the optimal state is to operate under conditions of constant returns to scale (CRS). However, the unit can also be efficient by operating with variable returns. The decision about the assumed scale effects should not be made arbitrarily. Simar and Wilson [2002] argued that when technology is not operating at CRS then estimating the measure of technical efficiency under CRS will lead to inconsistent results. Moreover, assuming CRS when VRS should be assumed in reality overestimates the technical efficiency estimate exactly by scale efficiency [Badunenko, Mozharovskyi, 2016]. Prior knowledge of the industry could be used to decide on the type of returns to scale, but where there is a lack of sufficient information about the process a statistical test can be implemented. Simar and Wilson [2002] proposed two versions of the test: the first version verifies the null hypothesis of CRS when the alternative hypothesis assumes VRS (SW test 1), while the second version verifies the null hypothesis of NIRS with the same alternative hypothesis (SW test 2). Both versions use a bootstrapping method. In the first variant, the statistic represents the ratio of the average measure of technical efficiency under the assumption of VRS and CRS technologies. If the null hypothesis is true, then the average distance between the VRS and CRS frontiers is small. If the alternative hypothesis is true, then the average distance between the VRS and CRS frontiers is large. When the null hypothesis is rejected, the second test can be performed to verify the hypothesis that the technology is globally NIRS [Badunenko, Mozharovskyi, 2016]. The selection of the type of scale effects in this study was made based on the results of these tests.

The environmental variables in the DEA method can be implemented in two ways. In the first approach, they can be attached directly to the vector of variables reflecting the inputs [Coelli et al., 2005]. Daraio and Simar [2005] propose smoothing-based, fully nonparametric methods for estimating conditional frontiers, in which the environmental variables affect the shape of the frontier. However, such a solution is advisable only if the aim is to assess the efficiency of the units, as it does not allow for identification of the influence of exogenous variables. The second approach that takes advantage of the environmental variables is the method proposed by Simar and Wilson [2007], in which no additional variables are introduced into the input vector, but the DEA scores are corrected based on environmental variables. The algorithm was primarily aimed at solving the problem of the bias generated when estimating models explaining the influence of exogenous factors, including environmental variables, on the efficiency scores in the DEA method.

In the context of the evaluation of Regional Innovation Systems using the DEA method, the literature proposed the use of multi-stage methods, especially a two-stage method in which two phases of the process of generating innovation are identified: the process of knowledge production and the process of knowledge commercialisation [Carayannis et al., 2015; Chen, Guan, 2012; Kaihua, Mingting, 2014]. In this case, the idea of the two-stage approach is based on the assumption that, in the first stage, the effects are most often represented by patent applications or obtained patents, which in themselves are not yet a functioning innovation. Only in the second phase can the concrete economic benefits of these patents be observed. Unfortunately, in the context of the presented study, it should be explained that access to complete patent data at the subregional level is limited. Moreover, the so-called patenting culture in Poland differs from those in many other countries, resulting in a relatively small number of patent applications, and for many NUTS 3 areas, the number of patents filed in a given year is equal to zero. Therefore, it was decided to use the one-step method without identifying the RIS' efficiency in the knowledge production process.

The RIS efficiency evaluation in Polish subregions was carried out for the 2005–2016 period. One possible approach in this case was to use data for all those years simultaneously, i.e. to conduct DEA analysis for all units and periods together. In this way the intertemporal efficiency frontier could be determined [Harris, Ozgen, Ozcan, 2000; Tulkens, Vanden Eeckaut, 1995], and it would then be assumed that the production-possibility frontier does not change year to year. However, taking into account various external factors, as well as macroeconomic processes (including the financial crisis after 2008) which affect the innovativeness of enterprises, we cannot make such an assumption in the context of assessing the effectiveness of RISs. Therefore, the DEA efficiency indicators were estimated separately for individual years.

Another issue that needs to be considered when constructing the DEA method is that in the process of creating an innovation, we deal with phenomena that require time, in other words, that are spread over time. Most often, the effects of inputs on innovation in a given year are not observed in the same year, but in the next year or even later. The solution used in this study was that the input variables included in the DEA method came from the period (t – 1), i.e. the year preceding the observations for the variables reflecting the outputs. Also, the values for the environmental variables included in the analysis came from the period (t – 1).

In the most commonly used solutions, the efficiency scores obtained by the output-oriented DEA are identified as Farrell distances [Farrell, 1957] and take values greater than or equal to 1. However, taking into account the interpretation in which the inefficiency is rather a negative phenomenon, it seems more reasonable to assign the value of 1 to efficient units (the units on the frontier) and values below 1 to inefficient units, to reflect the distance of individual units from this frontier. Such a distance, denoting the magnitude of inefficiency, can be recognised as the Shephard distance [Shephard, 1970]. In this study, the DEA performance scores were presented as reciprocals of the original indicators from the output-oriented DEA method.

The aim of the second stage in the presented study was to identify the characteristics of the RISs in subregions which affect their efficiencies. In much of the research that implements non-parametric efficiency analysis, a semi-parametric two-stage approach has been used. The solution combines the DEA efficiency measurement with a regression analysis that uses DEA estimated efficiency for the dependent variable. In the second stage of such applications, the censored or truncated regression (or even ordinary least squares) is used to regress the DEA scores produced in the first stage. Simar and Wilson [2007] proved that such a two-stage procedure suffers from severe flaws that render its results, and particularly statistical inference based on them, questionable. Most importantly, they highlight the fact that the estimated DEA scores are calculated from a common sample of data. However, treating these scores as if they were independent observations is not appropriate because of the problems related to the inference, which is invalid due to serial correlations [Badunenko & Tauchmann, 2019].

Simar and Wilson [2007] proposed two variants of a statistically grounded bootstrap-based two-stage estimator that eliminates these weaknesses. The regression in which the dependent variable is the DEA score is estimated as a truncated regression, not censored, as was the case in previous studies. This is designed to reflect the fact that while many units are identified as being fully efficient, their efficiency may differ significantly. Moreover, they propose to use a bootstrap correction of the primary scores, as a result of which a certain value of inefficiency is identified for each unit. Due to the assumption that the actual efficiency is unobservable because we do not know the real production-possibility frontier, what we get in the DEA method is the distance to the frontier estimated on the basis of the given sample. Additionally, the method yields estimated standard errors and confidence intervals that do not suffer from bias due to estimated efficiency scores being correlated.

Generally, the approach was dedicated to cross-sectional data. In our case, when dealing with a panel data set, the following strategy was implemented. In the first step, the DEA scores for each year were calculated separately using the Simar-Wilson method. Then, in the second step, the panel models for all the years were estimated. It was not possible to use the models with random effects (RE) due to the fact that it was not possible to make an assumption about the independence of the explanatory variables and disturbances in the model. This was confirmed by the Hausman specification test. Therefore, regressions with fixed time effects and with fixed regional effects at the NUTS 2 level were estimated. Both one-way (time effects only) and two-way model specifications were applied. In each case, in accordance with Simar and Wilson, the estimation was performed as a truncated regression with right-truncation at 1, as the distance was defined as the Shephard type.

Data and variables

In order to evaluate the efficiency of RISs in Polish subregions using the DEA method, it is necessary to define variables representing the INPUTS and the OUTPUTS in the process of creating innovation. The selection of appropriate variables was determined by the availability of relevant statistical data. For variables reflecting the outputs, the following were used:

1) ***ppinnov_share*** – the share (from the total number of enterprises in the subregion) of enterprises that have implemented product or process innovations in the last three years, including the current year,

2) ***nmprod_share*** – the share of new or modernised products sold or introduced to the market in industrial enterprises in the last three years (including the current year) from the total value of products sold in the current year.

On the other hand, the following were assumed as variables representing direct inputs on innovative activities:

1) ***innov_share*** – the share (from the total number of enterprises in the subregion) of enterprises that incurred expenditure on innovative activities in a given year,
2) ***coop_share*** – the share (from the total number of enterprises in the subregion) of enterprises that have established cooperation in the field of innovative activities in the last three years, including the current year.

As mentioned above, the second objective of the study was to identify the features of RISs that are important for the efficiency of creating innovations in subregions. In the DEA approach, all such factors can be considered as environmental variables that may affect the ability of a RIS to efficiently combine the consumed inputs to the produced outputs. The problem in RIS analyses is the limited knowledge of real determinants. Makkonen and van der Have [2012] reviewed the measures employed to construct regional composite innovation indexes and showed that the most commonly used indicators are patents, R&D activity, human capital, economic indicators and the labour market. Buesa et al. [2007], building on theoretical elements of RIS, distinguished four groups of indicators reflecting the following aspects: (1) firms and their internal organisation and inter-firm relationships and market structure; (2) support infrastructure for innovation; (3) public administration innovation-linked performance; and (4) the regional and national environment for innovation. In our case, the selection of variables was based primarily on a group of theories classified as the so-called "new regionalism" in which local structural and institutional factors are considered as determinants of the innovation potential [Golejewska, 2019]. The environmental variables reflecting the features of the region that may affect the efficiency of RISs were also selected according to the helix ecosystem model proposed by Carayannis et al. [2018]. The measures had to be assigned to the following RIS characteristics: innovative enterprises, R&D activities, innovative milieu, human capital, social capital and spatial proximity. Unfortunately, we were not able to find data that could represent all of the aforementioned categories at the NUTS 3 level in the official statistics. Some factors, such as the density of the road network (roads) or density of rail networks (railway), are published only for NUTS 2 units. An even bigger problem is that this also applies to variables reflecting the level of human capital or investment in the R&D sector. In one NUTS 2 region there are both highly urbanised and rural NUTS 3 metropolises, and it is inappropriate to assume the same level of transport network density and common share of people with a higher education for these areas. Therefore, the modelling only takes into account those variables for which data was available at the appropriate level of spatial aggregation. Finally, taking into account the concept of Regional Innovation Systems and data availability, the following environmental factors were defined and included in the DEA analysis:

1) ***gdp_total_rel*** – value of total GDP in the subregion,
2) ***gdp_percapita_rel*** – GDP per capita in the subregion,
3) ***wages_rel*** – average monthly remuneration in the subregion,
4) ***indust_share_rel*** – industry share in total VA of the subregion,
5) ***pop_dens_rel*** – population density in a given subregion,
6) ***unemp_rel*** – registered unemployment rate as a percentage of the working population,

and two factors were used as an approximation of the level of social capital in subregions:

7) ***crimes_rel*** – number of crimes per 1,000 inhabitants,
8) ***divorces_rel*** – number of divorces per 1,000 inhabitants.

All of these variables were expressed in relative terms as a relation to the average value of a given variable in all Polish subregions. The descriptive statistics of all the variables used in the analysis for the initial year (2005) and the final year (2016) are presented in Table 1.

Additionally, the impact of each of these factors in the process of introducing an innovation may be observed only after some time, similar to the inputs impact, and therefore they were introduced into the regressions in the form of values from the previous year (*t* – 1). Additionally, the set of explanatory variables includes a variable reflecting the level of urbanisation of a given subregion. All Polish subregions (72 units) were divided into three separate groups. The first group of 15 units are NUTS 3 regions with strong urban centres where the majority of the population live in urban clusters (***urban)***, while the second group includes regions with an average degree of urbanisation, i.e. regions with small cities of 26 units (***intermediate***), and the third group are 31 typically rural and agricultural regions with at least 50% of the population living in rural areas (***rural***) [Eurostat, 2018]. The group of intermediate units in regressions was taken as the reference group for the regressions.

Table 1. Descriptive statistics of the analysed variables

Variable	Measurement unit	Mean	Std. Dev.	Var. Coeff. (%)	Min	Max	Data source
		2005					
ppinnov_share	[%]	41.0	8.2	20.0	18.4	61.4	Statistics Poland in Szczecin (Regional Office)
nmprod_share	[%]	16.9	14.7	86.9	1.3	72.1	
innov_share	[%]	37.4	8.0	21.5	17.9	57.7	
coop_share	[%]	23.6	6.1	26.0	6.0	36.6	
gdp_total	PLN	13358.9	13528.5	101.3	3560.0	113461.0	Statistics Poland, Local Data Bank https://stat.gov.pl/en
gdp_percapita	PLN	22395.6	8588.2	38.3	14589.0	67104.0	
wages	PLN	2149.4	290.8	13.5	1810.6	3465.2	
indust_share	[%]	26.3	8.7	32.9	11.8	57.5	
pop_dens	pers. per km²	366.7	693.1	189.0	42.0	3275.0	
unemp	[%]	20.3	6.3	31.0	6.2	34.9	
crimes	per 1,000 inh.	36.5	12.4	34.0	12.0	78.9	
divorces	per 1,000 inh.	1.4	0.5	38.1	0.1	3.0	
		2016					
ppinnov_share	[%]	37.2	6.9	18.7	23.4	56.7	Statistics Poland in Szczecin (Regional Office)
nmprod_share	[%]	10.4	6.7	64.3	2.3	30.7	
innov_share	[%]	28.8	7.0	24.4	15.4	45.6	
coop_share	[%]	14.1	5.5	39.3	4.9	27.8	
gdp_total	PLN	25712.4	28326.0	110.2	6580.0	237710.0	Statistics Poland, Local Data Bank https://stat.gov.pl/en
gdp_percapita	PLN	42402.0	17999.3	42.4	24556.0	136648.0	
wages	PLN	3722.1	489.1	13.1	3150.5	5591.5	
indust_share	[%]	29.8	8.7	29.3	9.9	57.2	
pop_dens	pers. per km²	362.1	679.5	187.7	42.0	3372.0	
unemp	[%]	11.0	4.0	36.7	2.4	20.2	
crimes	per 1,000 inh.	20.1	6.1	30.3	10.9	39.7	
divorces	per 1,000 inh.	1.7	0.3	18.1	0.9	2.5	

Source: Author's own calculations.

Results of RIS efficiency assessment in Polish subregions

Testing the returns to scale type

The first step in the DEA analysis of RISs in subregions was the verification of assumptions regarding returns to scale. The results of two Simar and Wilson tests conducted separately for each year are presented in Table 2.

When interpreting the presented test results, it should be concluded that for the first test, in which the hypothesis of constant returns to scale was verified, the same decision was obtained in each year: the CRS have been rejected. However, for the second test, in which the null hypothesis assumes that we are dealing with non-increasing returns to scale, the null hypothesis was not rejected for each year. Hence, the decision was made that the DEA analysis should be carried out with the assumption of non-increasing returns.

Table 2. Results of the tests for the scale effects type in the DEA analysis

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
	SW test 1											
SW-statistic	1.165	1.104	1.197	1.199	1.127	1.273	1.137	1.217	1.214	1.206	1.272	1.365
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SW test 2											
SW-statistic	1.001	1.002	1.001	1.024	1.002	1.007	1.000	1.001	1.002	1.018	1.000	1.008
p-value	0.999	0.994	0.992	0.016	0.960	0.575	0.999	0.982	0.926	0.237	0.999	0.222

Source: Author's own calculations.

DEA results without environmental variables

The RIS efficiency scores were determined separately for each year using the DEA-NISR method with ***ppinnov_share*** and ***nmprod_share*** as outputs, and ***innov_share*** and ***coop_share*** as inputs. Table 3 shows the results for 72 Polish NUTS 3 subregions for selected years, obtained using both the first Simar-Wilson algorithm (DEA scores) and bias-corrected scores from the second algorithm (bias-corrected DEA scores). Measures are presented with the Shephard distance so the values lower than 1 indicate inefficient regions while the scores equal to 1 denote fully efficient units. The first algorithm identifies effective units in a given year – the scores shaded in the first six columns in Table 3. The situation is different in the second algorithm, in which a correction is made using a multi-stage bootstrapping method by applying the environmental variables, a certain degree of inefficiency for all units is identified. This means that, by assumption in the second approach, none of the RISs is classified as fully efficient. Hence, it is not possible to compare directly the results of the two methods. It turned out, however, that the correlation between DEA scores determined by both methods, assessed with the use of the linear correlation coefficient, is over 0.86, which means that there is a significant convergence of the scores, despite the fact that in the second approach, many more variables were taken into account. The interpretation of the DEA scores obtained for the analysed RISs is based primarily on the results of the first approach. Meanwhile, the bias-corrected DEA scores were taken into account in an attempt to identify the RIS characteristics that influenced their efficiency, and these results were treated as the robustness check for the regression of the DEA scores without bias-correction.

Table 3. DEA scores and bias-corrected DEA scores for RIS in Polish sub-regions in 2005–2016

		2005	2007	2009	2011	2013	2016	2005	2007	2009	2011	2013	2016
no	subregion	DEA scores						bias-corrected DEA scores					
1	krakowski	0.74	0.77	0.73	0.98	0.88	0.99	0.70	0.69	0.68	0.93	0.84	0.91
2	m. Kraków	0.81	0.81	0.89	0.97	0.87	0.81	0.77	0.74	0.85	0.95	0.84	0.76
3	nowosądecki	0.99	0.69	0.71	0.85	0.83	0.93	0.92	0.64	0.67	0.79	0.79	0.87
4	oświęcimski	0.69	0.74	0.82	0.89	0.97	0.85	0.66	0.70	0.78	0.85	0.92	0.81
5	tarnowski	0.71	0.79	0.83	1.00	0.83	0.96	0.67	0.73	0.78	0.84	0.78	0.91
6	nowotarski	0.71	0.82	1.00	0.69	0.83	0.84	0.67	0.69	0.80	0.68	0.77	0.79
7	bielski	0.98	0.80	0.88	0.84	0.92	1.00	0.90	0.77	0.82	0.80	0.81	0.81
8	bytomski	0.84	0.48	0.62	0.65	0.56	0.73	0.80	0.40	0.58	0.61	0.53	0.65
9	częstochowski	0.94	0.82	0.89	0.86	1.00	0.72	0.88	0.75	0.83	0.77	0.91	0.68
10	gliwicki	0.93	1.00	0.99	0.91	0.97	0.91	0.88	0.75	0.93	0.90	0.93	0.88
11	katowicki	0.92	0.69	0.92	0.83	0.72	0.69	0.89	0.66	0.87	0.81	0.69	0.67
12	rybnicki	0.78	0.78	0.93	0.77	0.69	0.77	0.74	0.73	0.89	0.73	0.65	0.74

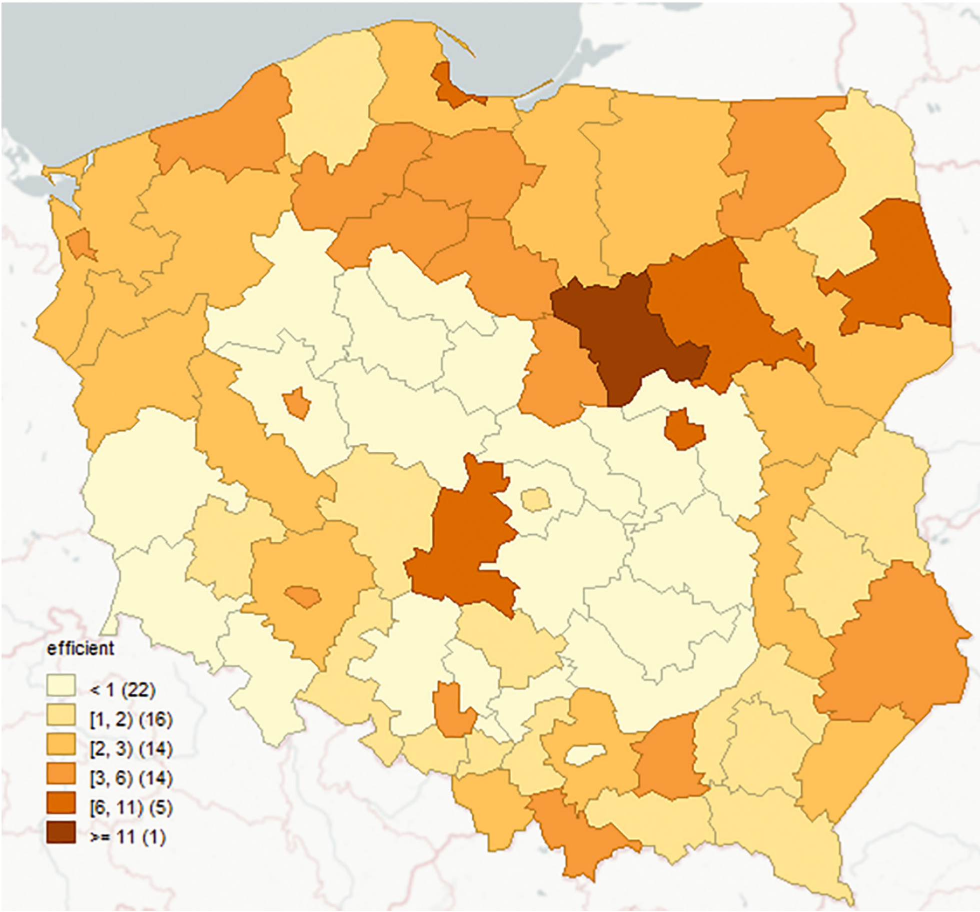
cont. Table 4

		2005	2007	2009	2011	2013	2016	2005	2007	2009	2011	2013	2016
no	subregion	DEA scores						bias-corrected DEA scores					
13	sosnowiecki	0.85	0.79	0.78	0.84	0.76	0.75	0.81	0.72	0.73	0.82	0.73	0.72
14	tyski	1.00	0.87	0.76	0.80	0.77	0.87	0.89	0.78	0.73	0.78	0.73	0.82
15	gorzowski	0.51	0.49	1.00	0.85	0.69	0.81	0.46	0.43	0.84	0.72	0.66	0.71
16	zielonogórski	0.76	0.71	0.70	0.73	0.78	0.86	0.72	0.63	0.66	0.70	0.75	0.81
17	kaliski	0.76	0.86	0.74	1.00	0.99	0.79	0.69	0.69	0.66	0.89	0.93	0.75
18	koniński	0.87	0.72	0.82	0.90	0.89	0.80	0.82	0.64	0.77	0.84	0.84	0.73
19	leszczyński	0.75	0.66	0.68	0.65	0.84	0.63	0.71	0.62	0.63	0.59	0.70	0.54
20	pilski	0.66	0.79	0.76	0.77	0.88	0.77	0.63	0.69	0.72	0.75	0.84	0.73
21	poznański	0.85	0.75	0.75	0.84	0.89	0.77	0.80	0.66	0.69	0.81	0.84	0.72
22	m. Poznań	1.00	0.74	0.79	0.97	1.00	0.89	0.86	0.69	0.75	0.94	0.84	0.84
23	koszaliński	1.00	1.00	0.82	0.76	0.88	0.88	0.64	0.66	0.77	0.68	0.82	0.82
24	szczecinecko-pyrzycki	0.87	1.00	0.83	0.68	0.82	0.53	0.75	0.79	0.78	0.64	0.76	0.50
25	m. Szczecin	0.82	0.48	0.64	0.78	0.80	1.00	0.70	0.43	0.57	0.74	0.75	0.78
26	szczeciński	0.61	0.72	0.77	0.71	1.00	0.76	0.55	0.64	0.74	0.66	0.93	0.72
27	jeleniogórski	0.84	0.72	0.82	0.74	0.95	0.80	0.79	0.63	0.78	0.70	0.90	0.74
28	legnicko- głogowski	0.89	0.57	0.98	0.61	0.74	0.98	0.85	0.53	0.94	0.59	0.70	0.85
29	wałbrzyski	0.78	0.78	0.81	0.72	0.87	0.76	0.74	0.71	0.78	0.68	0.84	0.71
30	wrocławski	0.69	0.87	0.90	0.89	0.91	0.79	0.66	0.80	0.86	0.85	0.86	0.74
31	m. Wrocław	0.81	0.79	0.82	1.00	0.93	0.84	0.77	0.72	0.77	0.97	0.91	0.79
32	nyski	0.77	0.76	0.78	0.84	0.84	0.87	0.74	0.68	0.75	0.80	0.80	0.83
33	opolski	0.78	0.80	0.89	0.79	0.88	0.80	0.76	0.75	0.85	0.77	0.84	0.77
34	bydgosko toruński	0.74	0.71	0.98	0.93	0.89	0.84	0.71	0.65	0.91	0.90	0.85	0.80
35	grudziądzki	0.78	0.59	0.91	0.81	1.00	1.00	0.75	0.52	0.82	0.74	0.85	0.59
36	włocławski	0.63	0.76	0.70	0.66	0.80	0.82	0.59	0.57	0.67	0.62	0.77	0.76
37	inowrocławski	0.39	0.40	0.80	0.82	0.76	0.73	0.36	0.37	0.76	0.80	0.73	0.69
38	świecki	0.94	0.73	1.00	0.94	0.95	0.61	0.87	0.67	0.85	0.85	0.89	0.50
39	gdański	0.84	0.71	0.72	0.95	0.96	0.91	0.79	0.59	0.67	0.85	0.83	0.86
40	słupski	0.94	0.63	1.00	0.85	0.71	0.93	0.86	0.57	0.83	0.77	0.68	0.65
41	starogardzki	0.98	0.82	1.00	0.97	1.00	0.88	0.89	0.61	0.85	0.88	0.87	0.73
42	trójmiejski	0.82	0.66	1.00	1.00	1.00	0.86	0.79	0.51	0.80	0.90	0.88	0.82
43	chojnicki	0.93	0.57	0.78	0.69	0.95	1.00	0.85	0.44	0.70	0.63	0.88	0.70
44	elbląski	0.85	1.00	0.82	0.76	0.95	0.73	0.80	0.64	0.75	0.70	0.91	0.70
45	ełcki	0.87	1.00	0.63	0.96	0.97	0.57	0.82	0.86	0.60	0.85	0.91	0.50
46	olsztyński	0.83	0.87	0.91	0.82	1.00	0.91	0.79	0.76	0.81	0.77	0.95	0.87
47	łódzki	0.59	0.81	0.70	0.77	0.77	0.79	0.56	0.65	0.66	0.71	0.73	0.74
48	m. Łódź	0.78	0.79	0.91	0.95	0.91	0.99	0.76	0.74	0.86	0.91	0.87	0.93
49	piotrkowski	0.92	0.83	0.76	0.84	0.92	0.67	0.87	0.71	0.72	0.78	0.88	0.62
50	sieradzki	1.00	1.00	1.00	1.00	1.00	0.74	0.83	0.73	0.88	0.88	0.89	0.61
51	skierniewicki	0.99	0.75	0.91	0.74	0.84	0.63	0.90	0.67	0.85	0.70	0.79	0.60
52	kielecki	0.81	0.73	0.88	0.91	0.83	0.69	0.77	0.64	0.82	0.86	0.80	0.65
53	sandomiersko jędrzejowski	0.90	0.89	0.77	0.84	0.81	0.74	0.88	0.80	0.73	0.79	0.77	0.68
54	bialski	0.89	0.80	0.85	0.57	0.85	0.82	0.75	0.64	0.75	0.51	0.79	0.77
55	chełmsko zamojski	0.66	0.65	0.78	1.00	0.96	1.00	0.62	0.53	0.70	0.89	0.89	0.77
56	lubelski	0.92	0.97	0.76	0.99	1.00	0.91	0.89	0.89	0.72	0.97	0.92	0.86
57	puławski	0.88	0.82	0.87	0.83	0.83	0.84	0.85	0.77	0.80	0.74	0.79	0.76
58	krośnieński	0.79	0.74	0.95	0.96	0.97	0.80	0.74	0.66	0.90	0.93	0.93	0.76
59	przemyski	0.91	0.84	1.00	1.00	0.78	0.89	0.83	0.76	0.93	0.94	0.74	0.85

		2005	2007	2009	2011	2013	2016	2005	2007	2009	2011	2013	2016
no	subregion	DEA scores						bias-corrected DEA scores					
60	rzeszowski	0.86	0.75	0.84	0.93	0.92	0.79	0.83	0.72	0.80	0.90	0.87	0.74
61	tarnobrzeski	0.90	0.87	1.00	0.92	0.92	0.92	0.87	0.79	0.94	0.90	0.88	0.85
62	białostocki	1.00	0.75	1.00	0.98	1.00	1.00	0.84	0.65	0.92	0.96	0.94	0.85
63	łomżyński	0.74	0.45	0.92	1.00	0.73	0.74	0.70	0.40	0.79	0.84	0.70	0.71
64	suwalski	1.00	0.60	0.54	0.48	0.78	0.96	0.91	0.55	0.52	0.45	0.72	0.91
65	cap. Warszawa	1.00	0.96	0.88	1.00	1.00	0.92	0.95	0.94	0.84	0.99	0.98	0.88
66	warszawski wschodni	0.90	0.85	0.86	0.91	0.98	0.83	0.86	0.78	0.82	0.86	0.91	0.73
67	warszawski zachodni	0.85	0.86	0.90	0.89	0.73	0.74	0.83	0.80	0.82	0.87	0.70	0.71
68	ciechanowski	1.00	1.00	1.00	0.64	1.00	1.00	0.73	0.62	0.73	0.58	0.85	0.76
69	ostrołęcki	0.75	0.78	1.00	1.00	0.98	1.00	0.72	0.67	0.82	0.86	0.90	0.75
70	radomski	0.81	0.81	0.81	0.72	0.80	0.58	0.75	0.75	0.78	0.68	0.76	0.52
71	płocki	1.00	0.69	0.86	0.66	1.00	0.87	0.83	0.66	0.79	0.62	0.90	0.77
72	siedlecki	0.84	0.77	0.60	0.76	1.00	0.84	0.81	0.72	0.58	0.73	0.91	0.78

Source: Author's own calculations using **simarwilson** STATA command [Badunenko, Tauchmann, 2019].

Figure 1. The number of years in which RIS was efficient, 2005–2016



Source: Author's own calculations.

As presented in Figure 1, it seems that 22 of the 72 subregions proved to be inefficient in each of the analysed years and 16 were efficient only once. The efficient subregions in the majority of the analysed years were Ciechanowski, Trójmiejski, Sieradzki and Białostocki. The lowest number of efficient units was in 2007 and 2016, with seven and eight respectively. The highest number, 18 units, was reported in 2014. The results confirm significant differences in the innovative efficiency of enterprises in Polish subregions. Most of the subregions remained inefficient during the analysed period, which means that the inputs involved did not match the obtained outputs. Over the 12-year period, the highest number of efficient cases was reported in Mazowieckie and Pomorskie (NUTS-2 regions), while the lowest numbers were recorded in Lubuskie, Opolskie and Podkarpackie, and there were none in the Świętokrzyskie region. In the area around the capital city of Warsaw, in the eastern Warsaw subregion and the western Warsaw subregion, enterprises were inefficient throughout the entire period. In most cases, subregions are not using their full potential, and there are subregions that in selected years used just over half of their potential. The efficiency of these subregions could be improved if the R&D expenditures resulted in commercialised products [Dzemydaitė et al., 2016]. Such a situation may be the result of the activity of innovators themselves as well as endogenous regional factors affecting innovative activity.

Efficiency versus productivity of RIS

As stated in the introduction, a unit's efficiency determined by the DEA method does not mean it has high productivity. Therefore, a RIS assessed as efficient may be efficient, but not highly productive (a weak RIS) or efficient and at the same time highly innovative (a strong RIS). In our study, the sum of the variables defined as outputs in the DEA was used to identify strong and weak RISs. Strong units were classified as subregions for which the sum of the outputs of innovation processes was higher than the average for all the subregions in a given year, and subregions with values lower than the average were identified as weak RISs. Table 4 presents the size of the following groups of subregions: efficient, strong-efficient and inefficient. The results were obtained when assessing efficiency using the DEA method without taking into account environmental variables (RIS characteristics) in the vector of inputs.

Table 4. Number of efficient, strong-efficient and inefficient RIS in 2005–2016 based on DEA method

year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
number of NUTS 3 regions												
efficient	9	13	7	14	11	10	9	9	13	18	12	8
efficient & strong	6	10	4	9	6	6	5	6	8	10	7	6
inefficient	63	59	65	58	61	62	63	63	59	54	60	64

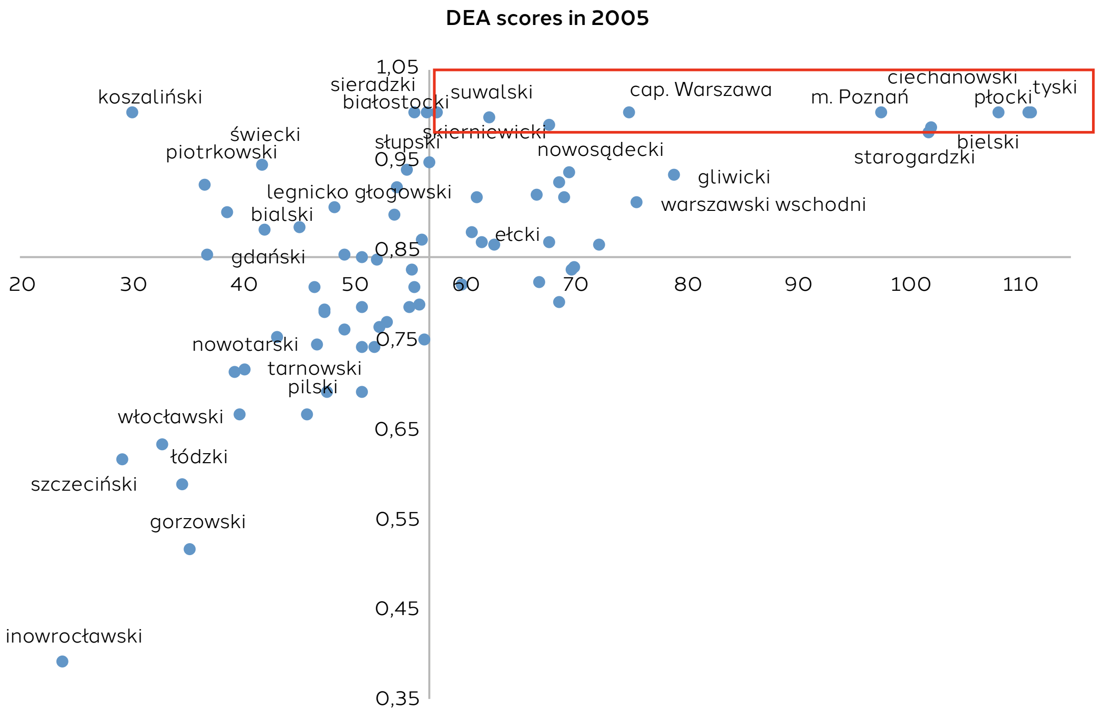
Source: Author's own calculations.

Figures 2 and 3 show the relationship between the variables reflecting RIS outputs (horizontal axes) and the evaluation of the efficiency of these systems obtained using the DEA method without environmental variables (vertical axes). Figure 2 shows the situation in the initial year (2005), while Figure 3 shows the situation in 2016. In this way, it is possible to identify subregions characterised by a high innovation effect and assessed as efficient, which means those that made maximum use of factors defined as inputs in the innovation process. The group of efficient subregions that achieve the highest innovation effect have been identified.

In 2005, the group of efficient and at the same time highly productive subregions consisted of six subregions: the capital Warszawa, Ciechanowski Tyski, Płocki, City of Poznań, and Suwalski. In 2016, the group included the City of Łódź, City of Szczecin, Bielski, Białostocki, Ostrołęcki and Legnicko-Głogowski. These are regions whose business innovation activity could be treated as a benchmark. In both analysed years, the largest group consists of inefficient and at the same time least productive units.

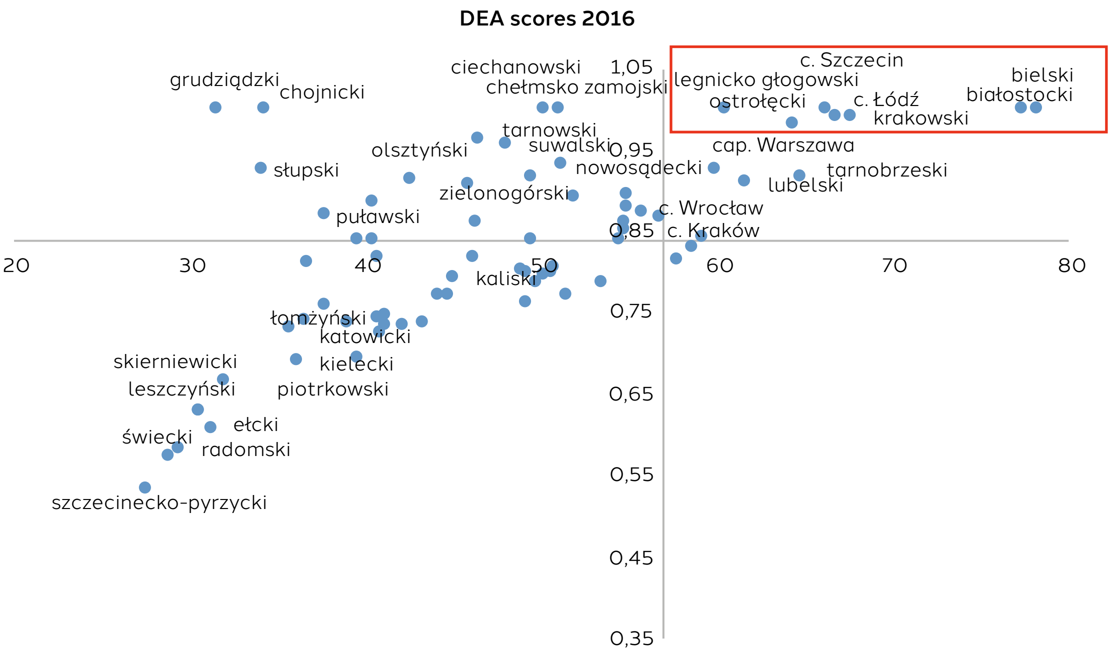
The obtained results seem surprising as it turns out that the most efficient regions were characterised by a rather lower level of development and a low rate of economic growth. Hence the question is what actually influences the economic growth of a given unit: whether the key factor is RIS efficiency or the productivity of innovative processes, which does not always have to be related to efficiency. Not every innovation is successful and not every effort is effective, but if there are no expenditures and no attempts are made, then there is no chance of success. In this analysis, the variables reflecting the innovation outputs are measured with the share of innovative companies and the share of innovative products, not their values. Perhaps, if we had information on revenues generated as a result of innovative activity, the results of the RIS efficiency assessment would be different.

Figure 2. RIS efficiency versus the level of innovation in 2005



Source: Author's own calculations.

Figure 3. RIS efficiency versus the level of innovation in 2016



Source: Author's own calculations.

Identification of RIS features affecting efficiency

The last stage of the study was the estimation of econometric models in which the DEA results were the dependent variable. Of course, from the two approaches presented above, only the results of the DEA method without environmental variables could be modelled. Table 5 presents the results of estimating various regression variants, taking into account the previously described variables reflecting the RIS features. Due to the high correlation between some of the variables, three separate variants were shown in which total GDP, GDP per capita or wages were taken into account. In addition, in order to control the specificity of individual years, e.g. accounting for the economic crisis, periodic specific effects were also introduced as fixed effects. Due to the fact that we also assume that assigning each NUTS 3 region to a given voivodeship may be important, in the specifications (2), (4), (6) and later (8), (10), (12), the specific effects for the NUTS 2 region were taken into account.

Table 5. Regression of the uncorrected DEA scores for the 72 NUTS 3 panel, 2005–2016

	dependent: ***uncorrected DEA scores***					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
rural	−0.046*** (0.013)	−0.057*** (0.014)	−0.052*** (0.013)	−0.062*** (0.014)	−0.051*** (0.013)	−0.065*** (0.014)
urban	−0.035* (0.020)	−0.069*** (0.023)	−0.038* (0.020)	−0.071*** (0.023)	−0.039* (0.020)	−0.068*** (0.023)
gdp_total_rel$_{t-1}$	0.026** (0.011)	0.033*** (0.012)				
gdp_percapita_rel$_{t-1}$			0.038 (0.026)	0.055* (0.030)		
wages_rel$_{t-1}$					0.081 (0.063)	0.075 (0.072)
indust_share_rel$_{t-1}$	0.027 (0.018)	0.034* (0.021)	0.018 (0.020)	0.016 (0.023)	0.023 (0.019)	0.027 (0.022)
unemp_rel$_{t-1}$	−0.023 (0.020)	−0.041* (0.021)	−0.025 (0.021)	−0.041* (0.023)	−0.029 (0.020)	−0.051** (0.022)
pop_dens_rel$_{t-1}$	0.020*** (0.006)	0.008 (0.006)	0.022*** (0.006)	0.010 (0.006)	0.024*** (0.005)	0.015*** (0.006)
crimes_rel$_{t-1}$	−0.048* (0.027)	0.041 (0.032)	−0.060** (0.027)	0.020 (0.031)	−0.062** (0.027)	0.017 (0.031)
divorces_rel$_{t-1}$	−0.075*** (0.025)	−0.065** (0.029)	−0.078*** (0.025)	−0.066** (0.029)	−0.075*** (0.025)	−0.066** (0.029)
constant	0.932*** (0.044)	0.840*** (0.060)	0.947*** (0.045)	0.862*** (0.061)	0.899*** (0.070)	0.839*** (0.081)
sigma	0.112*** (0.004)	0.108*** (0.004)	0.112*** (0.005)	0.108*** (0.004)	0.112*** (0.004)	0.108*** (0.004)
chi^2	102.3	150.9	107.8	153.9	107.1	153.5
observations	731	731	731	731	731	731
regional effects	no	yes	no	yes	no	yes
time effects	yes	yes	yes	yes	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimation method: MLE for truncated regression for panel data model.

Source: Author's own calculations.

For a robustness check of the conclusions for the selection of the DEA evaluation method, Table 6 presents the regression estimation results explaining the variability of DEA scores corrected in accordance with Simar and Wilson's 2nd algorithm. It turns out that the conclusions regarding the impact of RIS features on efficiency do not differ significantly.

Table 6. Regression of the bias-corrected DEA scores

	dependent: ***bias-corrected DEA scores***					
VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
rural	−0.041*** (0.010)	−0.050*** (0.011)	−0.047*** (0.009)	−0.055*** (0.010)	−0.044*** (0.009)	−0.056*** (0.010)
urban	−0.022 (0.016)	−0.049*** (0.017)	−0.024 (0.016)	−0.050*** (0.017)	−0.026 (0.016)	−0.049*** (0.017)
gdp_total_rel $_{t-1}$	0.025*** (0.009)	0.026*** (0.009)				
gdp_percapita_rel $_{t-1}$			0.041** (0.020)	0.049** (0.023)		
wages_rel $_{t-1}$					0.164*** (0.048)	0.121** (0.056)
indust_share_rel $_{t-1}$	0.032** (0.014)	0.043*** (0.016)	0.022 (0.015)	0.026 (0.018)	0.020 (0.015)	0.028* (0.017)
unemp_rel $_{t-1}$	−0.030** (0.015)	−0.039** (0.017)	−0.029* (0.015)	−0.037** (0.018)	−0.028* (0.015)	−0.040** (0.017)
pop_dens_rel $_{t-1}$	0.019*** (0.004)	0.011** (0.005)	0.022*** (0.005)	0.013*** (0.005)	0.021*** (0.004)	0.016*** (0.004)
crimes_rel $_{t-1}$	−0.055*** (0.020)	0.021 (0.023)	−0.070*** (0.020)	−0.001 (0.023)	−0.076*** (0.020)	−0.007 (0.023)
divorces_rel $_{t-1}$	−0.049*** (0.018)	−0.022 (0.022)	−0.054*** (0.019)	−0.025 (0.022)	−0.054*** (0.019)	−0.029 (0.022)
constant	0.853*** (0.033)	0.751*** (0.046)	0.867*** (0.033)	0.772*** (0.046)	0.749*** (0.052)	0.710*** (0.063)
sigma	0.101*** (0.003)	0.096*** (0.003)	0.101*** (0.003)	0.096*** (0.003)	0.101*** (0.003)	0.096*** (0.003)
chi^2	265.4	378.7	277.9	387.2	282.4	390.8
observations	864	864	864	864	864	864
regional effects	no	yes	no	yes	no	yes
time effects	yes	yes	yes	yes	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimation method: MLE for truncated regression for panel data model.

Source: Author's own calculations.

Assessing the importance of the **innovative milieu**, the results confirm the statistically significant positive impact of total GDP in a subregion, which was used as a proxy for market size. Innovations are generated by enterprises for profit, so there should be demand for innovation determined by factors including market capacity [Buesa et al., 2007]. However, the influence of the **standard of living** in the region, expressed by the level of GDP per capita and the level of wages, was not fully confirmed by the results. The estimates were statistically significant only for the corrected DEA scores, at which point the impact appeared to be positive. Also, the unemployment rate, another measure of the standard of living, turns out to have a negative influence on the efficiency of innovative processes. This influence was confirmed in both uncorrected and corrected DEA scores. As unemployment increases, the purchasing power of society decreases, which may be reflected in reduced demand for innovation and its lower supply from local enterprises. Public procurement articulating quality requirements for new products and services and the activation of local companies through innovative projects based on public-private partnerships could help subregions facing limited demand for innovation.

It was not fully confirmed that the share of industrial enterprises in the total number of enterprises significantly influenced the effectiveness of a RIS. This may suggest that innovation expenditures incurred in industry and established cooperation on innovation projects are just as efficient as those in the service sector. This should be taken into account in policies directed towards support programmes which are regionally oriented as well as those tailored to the needs of individual regions with diversified production structures. This mainly applies to support offered by EU structural funds. The results for **spatial proximity**, reflected by population density, indicate that a higher population density has a positive effect on the innovation efficiency of regions. Thus, it can be assumed that geographical proximity and direct interactions enhance the knowledge diffusion effect. Moreover, it turns out that in almost every specification for both models, the level of urbanisation in the subregion had an impact on the efficiency of the RIS. The scores were lower in the least urbanised regions, but also in the most urbanised ones compared to units with an average level of urbanisation. This may suggest that the specificity of a RIS is different in urban and rural regions. It is a confirmation that most innovations are created in cities which, in contrast to poorly urbanised areas, are characterised by high institutional density, which induces innovation. This may indicate that, due to the limited number of institutions supporting knowledge transfer in rural areas, farmers' social networks may be of key importance for generating innovation.

Finally, interpreting the results for **social capital**, we can state that it was an important component of regional innovation systems. It is assumed that good social relationships facilitate knowledge transfers, while a lack of relationships or bad relationships do not [Golejewska, 2019]. The number of crimes and the number of divorces were used as an approximation of social capital. The estimates of the parameters for both variables in most of the specifications turned out to be statistically significant and negative, which means that the negative elements of social capital reduce the efficiency of the innovation process. This may suggest that a lack of trust and social relationships leads to increased transaction costs and reduced interaction, resulting in a decreased innovation performance of enterprises. It has been increasingly recognised that the social capital of the business sector and its actors, and their relationships to actors in other sectors, has a significant impact on regional development. However, the role of the government, its norms, values and networks cannot be overlooked. In order to support regional innovation, a region's social capital should adapt to changes in the region's business and production structure. However, this does not mean that all of the components of the "old" social capital shaped by a region's history are redundant. This is because they create the stability of networks and values without which regional cohesion would be unsafe. Thus, the appropriate social capital is an optimal combination of different vintages.

Conclusions

Generally, the hypothesis of the diverse influence of regional environmental elements on the technological efficiency of firms has been confirmed. The results of the analysis have proven the positive impact of regional market size, standard of living and social proximity on the efficiency of innovation processes in Poland. It has been confirmed that the negative elements of social capital reduce the efficiency of RISs. In contrast, the impact of GDP per capita, wages, and the share of industrial enterprises was not fully confirmed by the results. The group of strong RISs turned out to be small in the analysed years. The higher the technological level of a region, the higher the need for system coordination. According to the literature, regions with lower absorptive capacity capture knowledge and innovation from other regions [Zabala-Iturriagagoitia et al., 2007]. There is a clear dominance of inefficient RISs in Poland.

The social aspect, important for technological efficiency, needs to be improved, especially in post-communist countries where it has been neglected for a long time [Nowakowska, 2011]. The results of the literature review indicate a lack of such comprehensive analyses for RISs in Poland and other Central and Eastern European countries. They can be regarded as necessary from the point of view of regional policy planning with regards to competitiveness and innovativeness, its main determinant. In Poland, regional innovation policy has been "forced" to a large extent by external conditions, including European funds. The bottom-up needs and reorientation of regional policy were less important. Increasing the effectiveness of the innovative capacity of regions depends on several factors, including stable regional structures and trust among regional partners. The use of temporary solutions and relegating innovation policy to the margins of regional authorities' activities is definitely not conducive to such efforts.

Economists try to analyse the structure and performance of regions, looking for optimal development paths. Among the models, one can distinguish performance, process and policy benchmarking. The first type is based on a comparison of indicators reflecting the most important features of the analysed regions; the second reflects the structures and systems that determine the practices and functioning of the regions; and the last one involves the types of policies that influence the nature of practices and characteristics of the studied regions. The task of policy makers, however, should not be to imitate models of regional development without taking into account the region-specific context. In line with the observed trends, innovation policy is characterised by a high degree of generalisation and reliance on a limited set of regional experiences. The basic problems of regional policy in terms of imitating best practice are often subtle interdependencies between different "elements" of the region. This should be taken into account when using the results of this analysis in practice. A regional innovation system is not an objective in itself. It should rather be treated as a type of regional policy stimulating the capacity of innovative companies in a region. Taking into account the determinants of its efficiency and productivity within the EU's cohesion policy seems to be fundamental. When formulating the objectives of EU cohesion policy in the case of Central and Eastern European countries, special attention should be paid to social relations, which can prevent fragmentation of systems and result in an improved innovative position of regions. The need for a differentiated approach in EU cohesion policy remains unquestionable. However, it would also be useful to examine which of the analysed categories – efficiency or productivity – has a stronger impact on subregional development. This will be the subject of future analysis.

We would like to acknowledge that our analysis has some limitations. First and foremost, due to the nature of the available data set, it does not include important analysis indicators for RISs, such as measures of human capital and institutions. Another limitation is the relatively short time frame of the analysis. Further research is therefore necessary.

References

Asheim B. T., Coenen L. [2005], Knowledge bases and regional innovation systems: Comparing Nordic clusters, *Research Policy*, 34 (8): 1173–1190, https://econpapers.repec.org/RePEc:eee:respol:v:34: y:2005: i:8: p:1173–1190 (accessed on 4.05.2021).

Asheim B. T., Gertler M. S. [2009], The Geography of Innovation: Regional Innovation Systems, in: Fagerberg J., Mowery D. C. (eds.), *The Oxford Handbook of Innovation*: 291–317, Oxford University Press, New York, https://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780199286805.001.0001/oxfordhb-9780199286805-e-11 (accessed on 4.05.2021).

Asheim B. T., Isaksen, A. [2002], Regional innovation systems: The integration of local "sticky" and global "ubiquitous" knowledge, *Journal of Technology Transfer*, 27 (1): 77–86, https://link.springer.com/article/10.1023/A:1013100704794 (accessed on 4.05.2021).

Badunenko O., Mozharovskyi P. [2016], Nonparametric frontier analysis using Stata, *The Stata Journal*, 16 (3): 550–589.

Badunenko O., Tauchmann H. [2019], Simar and Wilson two-stage efficiency analysis for Stata, *The Stata Journal*, 19 (4): 950–988.

Banker R. D., Charnes A., Cooper W. W. [1984], Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, 30 (9): 1078–1092, https://pubsonline.informs.org/doi/abs/10.1287/mnsc.30.9.1078 (accessed on 22.01.2021).

Banker R. D., Natarajan R. [2008], Evaluating contextual variables affecting productivity using data envelopment analysis, *Operations Research*, 56 (1): 48–58.

Barca F. [2009], *An agenda for a reformed Cohesion Policy: A place-based approach to meeting European Union challenges and expectations*, Independent Report prepared at the request of Danuta Hübner, Commissioner for Regional Policy.

Biorn E., Hagen T. P., Iversen T., Magnussen J. [2002], The Effect of Activity-Based Financing on Hospital Efficiency: A Panel Data Analysis of DEA Efficiency Scores 1992–2000, *Health Care Management Science*, 6 (4): 271–283.

Braczyk H.-J., Cooke P., Heidenreich M. [1998], *Regional Innovation Systems: The Role of Governances in a Globalized World*, UCL Press, London, https://www.routledge.com/Regional-Innovation-Systems-The-Role-of-Governances-in-a-Globalized-World/Braczyk-Cooke-Heidenreich/p/book/9780415303699 (accessed on 4.05.2021).

Brandt N. [2018], *Strengthening innovation in Poland*, 1479, OECD Economics Department Working Papers, https://www.oecd-ilibrary.org/economics/strengthening-innovation-in-poland_abf2c877-en (accessed on 4.05.2021).

Buesa M., Martínez-Pellitero M., Baumert T., Heijs J. [2007], Novel Applications of Existing Econometric Instruments to Analyse Regional Innovation Systems: The Spanish Case, in: Surinach R., Moreno R., Vayá E. (eds.), *Knowledge Externalities, Innovation Clusters and Regional Development*: 155–175, Edward Elgar, Cheltenham.

Carayannis E.G., Goletsis Y., Grigoroudis E. [2015], Multi-level multi-stage efficiency measurement: The case of innovation systems, *Operational Research*, 15 (2): 253–274, https://www.infona.pl//resource/bwmeta1.element.springer-66b84f4f-ecce-39c2-b8ab-0e7647920a65 (accessed on 22.01.2021).

Carayannis E.G., Grigoroudis E., Campbell D.F.J., Meissner D., Stamati D. [2018], The ecosystem as helix: an exploratory theory-building study of regional co-opetitive entrepreneurial ecosystems as Quadruple/Quintuple Helix Innovation Models, *R&D Management*, 48 (1): 148–162, https://onlinelibrary.wiley.com/doi/full/10.1111/radm.12300 (accessed on 27.08.2021)

Carlsson B., Jacobsson S., Holmen M., Rickne A. [2002], Innovation systems: analytical and methodological issues, *Research Policy*, 31 (2), 233–245, https://econpapers.repec.org/RePEc:eee:respol:v:31:y:2002:i:2: p:233–245 (accessed on 4.05.2021).

Carlsson B., Stankiewicz R. [1991], On the nature, function and composition of technological systems, *Journal of Evolutionary Economics*, 1 (2): 93–118, https://link.springer.com/article/10.1007/BF01224915 (accessed on 4.05.2021).

Charnes A., Cooper W.W., Rhodes E. [1978], Measuring the efficiency of decision making units, *European Journal of Operational Research*, 2 (6): 429–444.

Chen K., Guan J. [2012], Measuring the efficiency of China's regional innovation systems: Application of network data envelopment analysis (DEA), *Regional Studies*, 46 (3): 355–377, https://www.tandfonline.com/doi/abs/10.1080/00343404.2010.497479 (accessed on 22.01.2021).

Coelli T.J., Prasada Rao D.S., O'Donnell C.J., Battese G.E. [2005], *An introduction to efficiency and productivity analysis. An Introduction to Efficiency and Productivity Analysis*, vol. 2, Springer US.

Cooke Ph. [2001], *Strategies for Regional Innovation Systems: Learning Transfer and Applications*, https://www.google.com/search?q=Cooke,+Ph.+2001.+Strategies+for+Regional+Innovation+Systems:+Learning+Transfer+and+Applications,+Centre+for+Advanced+Studies,+NIDO+World+Industrial+Development+Report+ (WDR) &spell=1&sa=X&ved=2ahUKEwj3hKerqLDwAhUR2SoKHVd6CHMQBSgAegQIARA1&biw=1536&bih=735 (accessed on 4.05.2021).

Cooke Ph., Boekholt P., Tödtling F. [1999], *The governance of innovation in Europe: regional perspectives on global competitiveness*, Pinter, New York, https://wellcomecollection.org/works/ff6dktg5 (accessed on 4.05.2021).

Ćwiąkała-Małys A., Nowak W. [2009], Sposoby klasyfikacji modeli DEA, *Badania Operacyjne i Decyzje*, 3: 5–18.

Daraio C., Simar L. [2005], Introducing environmental variables in nonparametric frontier models: A probabilistic approach, *Journal of Productivity Analysis*, 24 (1): 93–121, https://link.springer.com/article/10.1007/s11123-005-3042–8 (accessed on 3.02.2021).

De Bruijn P., Lagendijk A. [2005], Regional Innovation Systems in the Lisbon Strategy, *European Planning Studies*, 13 (8): 1153–1172, https://www.tandfonline.com/doi/abs/10.1080/09654310500336519 (accessed on 4.05.2021).

De Laurentis C. [2006], Regional innovation systems and the labour market: A comparison of five regions, *European Planning Studies*, 14 (8): 1059–1084, https://www.tandfonline.com/doi/abs/10.1080/09654310600852373 (accessed on 4.05.2021).

Diez M.A., Esteban M.S. [2000], The evaluation of regional innovation and cluster policies: looking for new approaches, *Fourth EES Conference*, Lausanne.

Doloreux D., Dionne S. [2008], Is regional innovation system development possible peripheral regions? Some evidence from the case La Pocatière, Canada, *Entrepreneurship and Regional Development*, 20 (3): 259–283, https://www.tandfonline.com/doi/abs/10.1080/08985620701795525 (accessed on 4.05.2021).

Doloreux D., Parto S. [2005], Regional innovation systems: Current discourse and unresolved issues, *Technology in Society*, 27 (2): 133–153, www.elsevier.com/locate/techsoc (accessed on 4.05.2021).

Domagała A. [2007], Przestrzenno-czasowa analiza efektywności jednostek decyzyjnych metodą Data Envelopment Analysis Envelopment Analysis Envelopment Analysis na przykładzie banków polskich, *Badania Operacyjne i Decyzje*, 3–4: 35–56.

Dzemydaitë G., Dzemyda I., Galinienë B. [2016], The Efficiency of Regional Innovation Systems in New Member States of the European Union: A Nonparametric DEA Approach, *Economics and Business*, 28 (1): 83–89.

Dziallas M., Blind K. [2019], Innovation indicators throughout the innovation process: An extensive literature analysis, *Technovation*, 80–81: 3–29.

EBRD [2019], *The financial crisis and the EBRD*, https://www.ebrd.com/what-we-do/sectors-and-topics/financial-crisis.html (accessed on 4.10.2020).

Edquist C. [2000], System of innovation approaches – their emergence and characteristics, in: Edquist C. (ed.), *Systems of Innovation, Technologies, Institutions and Organizations*: 1–35, Routledge, London.

Edquist C. [2014], *Efficiency of Research and Innovation Systems for Economic Growth and Employment*, 8, *Papers in Innovation Studies*, Lund University, CIRCLE – Centre for Innovation Research, https://ideas.repec.org/p/hhs/lucirc/2014_008.html (accessed on 4.05.2021).

European Commission [2018], Economic and Social Committee and the Committee of the Regions, *A renewed European Agenda for Research and Innovation: Europe's chance to shape its future, The European Commission's contribution to the informal EU leaders' meeting on innovation in Sofia on 16 May 2018*, Brussels.

Eurostat [2018], *Methodological manual on territorial typologies 2018 edition*, Luxembourg.

Eurostat [2019], EU policies for regions and cities, *Statistics Explained*, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:EU_policies_for_regions_and_cities (accessed on 12.12.2019).

Färe R., Lovell K. C. A. [1978], Measuring the technical efficiency of production, *Journal of Economic Theory*, 19 (1): 150–162.

Farrell M. J. [1957], The Measurement of Productive Efficiency, *Journal of the Royal Statistical Society. Series A (General)*, 120 (3): 290.

Fernández-Serrano J., Martínez-Román J. A., Romero I. [2019], The entrepreneur in the regional innovation system. A comparative study for high- and low-income regions, *Entrepreneurship and Regional Development*, 31 (5–6): 337–356, https://www.tandfonline.com/doi/abs/10.1080/08985626.2018.1513079 (accessed on 4.05.2021).

Fischer M. M. [2001], Innovation, knowledge creation and systems of innovation, *The Annals of Regional Science*, 35 (2): 199–216, https://ideas.repec.org/a/spr/anresc/v35y2001i2p199–216.html (accessed on 4.05.2021).

Fritsch M. [2004], Cooperation and the efficiency of regional R&D activities, *Cambridge Journal of Economics*, 28 (6): 829–846.

Fritsch M., Slavtchev V. [2006], *Measuring the efficiency of regional innovation systems: an empirical assessment*, 8, *Freiberg Working Papers*, TU Bergakademie Freiberg, Faculty of Economics and Business Administration, https://ideas.repec.org/p/zbw/tufwps/200608.html (accessed on 4.05.2021).

Gertler M. S. [2003], Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there) on JSTOR, *Journal of Economic Geography*, 3 (1): 75–99, https://www.jstor.org/stable/26160465? seq=1 (accessed on 4.05.2021).

Golejewska A. [2019], *Regionalne Systemy Innowacji w Polsce. Funkcjonowanie, efektywność i perspektywy rozwoju*, Wydawnictwo Uniwersytetu Gdańskiego, Gdańsk.

Hajek P., Henriques R., Hajkova V. [2014], Visualising components of regional innovation systems using self-organizing maps – Evidence from European regions, *Technological Forecasting and Social Change*, 84 (C): 197–214.

Harris J., Ozgen H., Ozcan Y. [2000], Do mergers enhance the performance of hospital efficiency?, *Journal of the Operational Research Society*, 51 (7): 801–811, https://www.tandfonline.com/doi/abs/10.1057/palgrave.jors.2600869 (accessed on 22.01.2021).

Howells J. R. L. [2002], Tacit knowledge, innovation and economic geography, *Urban Studies*, 39 (5–6): 871–884, https://journals.sagepub.com/doi/10.1080/00420980220128354 (accessed on 4.05.2021).

Hsieh H. F., Shanno S. E. [2005], Three approaches to qualitative content analysis, *Qualitative Health Research*, 15 (9): 1277–1288, https://journals.sagepub.com/doi/10.1177/1049732305276687 (accessed on 4.05.2021).

Kaihua C., Mingting K. [2014], Staged efficiency and its determinants of regional innovation systems: A two-step analytical procedure, *Annals of Regional Science*, 52 (2): 627–657, https://link.springer.com/article/10.1007/s00168-014-0604-6 (accessed on 22.01.2021).

Kondratiuk-Nierodzińska M. [2013], *Regionalne systemy innowacji a konkurencyjność województw w Polsce*, Wydawnictwo Uniwersytetu w Białymstoku, Białystok.

Kozuń-Cieślak G. [2012], Efektywność wydatków publicznych na ochronę zdrowia w krajach Unii Europejskiej, *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 262: 188–201.

Krätke S. [2002], Network analysis of production clusters: The Potsdam/Babelsberg film industry as an example, *European Planning Studies*, 10 (1): 27–54, https://www.tandfonline.com/doi/abs/10.1080/09654310120099254 (accessed on 4.05.2021).

Kruczkowska E., Poniński T., Gileta K., Rzepka J., Szybisty B., Zając J. [2017], *Państwa Grupy Wyszehradzkiej europejskim centrum innowacji. Ekosystem i finansowanie*, Polski Fundusz Rozwoju, Warszawa.

Kumbhakar S. C., Lovell C. A. K. [2000], *Stochastic Frontier Analysis. Stochastic Frontier Analysis*, Cambridge University Press, Cambridge, https://www.cambridge.org/core/books/stochastic-frontier-analysis/510E56C2F890A0E6B38B4C4B241645B6 (accessed on 22.01.2021).

Lafarga C. V., Balderrama J. I. L. [2015], Efficiency of Mexico's regional innovation systems: An evaluation applying data envelopment analysis (DEA), *African Journal of Science, Technology, Innovation and Development*, 7 (1): 36–44, https://www.tandfonline.com/doi/abs/10.1080/20421338.2014.979652 (accessed on 4.05.2021).

Makkonen T., Have R. P. van der [2012], Benchmarking regional innovative performance: composite measures and direct innovation counts, *Scientometrics*, 94 (1): 247–262, https://link.springer.com/article/10.1007/s11192-012-0753-2 (accessed on 27.08.2021).

Mandl U., Dierx A., Ilzkovitz F. [2008], *The effectiveness and efficiency of public spending*, 301, European Economy, Economic Papers, Brussels, http://ec.europa.eu/economy_finance/publications (accessed on 3.02.2021).

Markard J., Truffer B. [2008], Technological innovation systems and the multi-level perspective: Towards an integrated framework, *Research Policy*, 37 (4): 596–615, https://econpapers.repec.org/RePEc:eee:respol:v:37: y:2008: i:4: p:596–615 (accessed on 4.05.2021).

Masternak-Janus A., Rybaczewska-Błażejowska M. [2016], Analiza efektywności innowacyjnej przedsiębiorstw przemysłowych w Polsce z wykorzystaniem metody DEA, in: Knosala R. (ed.), *Innowacje w zarządzaniu i inżynierii produkcji*: 493–503, Oficyna Wydawnicza PTZP, Opole.

Nowakowska A. [2011], *Regionalny wymiar procesów innowacji*, Wydawnictwo Uniwersytetu Łódzkiego, Łódź.

Paci R., Usai S. [2000], Technological enclaves and industrial districts: An analysis of the regional distribution of innovative activity in Europe, *Regional Studies*, 34 (2): 97–114, https://www.tandfonline.com/doi/abs/10.1080/00343400050006032 (accessed on 4.05.2021).

Plawgo B., Klimczak T., Czyż P., Boguszewski R., Kowalczyk A. [2013], *Regionalne systemy innowacji w Polsce – raport z badań*, PARP, Warszawa.

Roelandt T.J., Hertog P. den [1999], Cluster analysis and cluster-based policy making in OECD countries: An introduction to the theme, *OECD Boosting Innovation: The cluster approach*: 9–23, OECD, Paris, http://www.sciepub.com/reference/105327 (accessed on 4.05.2021).

Shephard R.W. [1970], *Theory of Cost and Production Functions*, Princeton University Press, Princeton, https://press.princeton.edu/books/hardcover/9780691647524/theory-of-cost-and-production-functions (accessed on 3.02.2021).

Simar L., Wilson P.W. [2002], Non-parametric tests of returns to scale, *European Journal of Operational Research*, 139 (1): 115–132.

Simar L., Wilson P.W. [2007], Estimation and inference in two-stage, semi-parametric models of production processes, *Journal of Econometrics*, 136 (1): 31–64, https://econpapers.repec.org/RePEc:eee:econom:v:136: y:2007: i:1: p:31–64 (accessed on 22.01.2021).

Stejskal J., Hajek P. [2015], Modelling knowledge spillover effects using moderated and mediation analysis – the case of Czech high-tech industries, in: *10th international conference on knowledge management in organizations*, Maribor, KMO, Slovenia.

Stejskal J., Kuvíková H., Meričková B.M. [2018], Regional Innovation Systems Analysis and Evaluation: The Case of the Czech Republic, in: Stejskal J., Hajek P., Hudec O. (eds.), *Advances in Spatial Science*: 81–113, Springer International Publishing, https://doi.org/10.1007/978-3-319-67029-4_3.

Sternberg R. [2007], Entrepreneurship, proximity and regional innovation systems, *Tijdschrift voor Economische en Sociale Geografie*, 98 (5): 652–666.

Szymańska E. [2010], Efektywność przedsiębiorstw – definiowanie i pomiar, *Roczniki Nauk Rolniczy*ch, seria G, 97 (2): 152–164.

Świadek A. [2011], *Regionalne systemy innowacji w Polsce*, Difin, Warszawa.

Tulkens H., Vanden Eeckaut P. [1995], Non-parametric efficiency, progress and regress measures for panel data: Methodological aspects, *European Journal of Operational Research*, 80 (3): 474–499.

Wojnicka-Sycz E. [2020], *Paradygmat systemowy w innowacyjnosci. Geneza, ewolucja i ocena*, Wydawnictwo Uniwersytetu Gdańskiego, Gdańsk.

Zabala-Iturriagagoitia J.M., Voigt P., Gutiérrez-Gracia A., Jiménez-Sáez F. [2007], Regional innovation systems: How to assess performance, *Regional Studies*, 41 (5): 661–672.

Żółtaszek A., Olejnik A. [2017], *Regional Effectiveness of Innovation – Leaders and Followers of the EU NUTS 0 and NUTS 2 Regions*, 8, Lodz Economic Working Papers, Łódź.