Scientometrics
https://doi.org/10.1007/s11192-019-03130-y

An assessment of regional innovation system efficiency in Russia: the application of the DEA approach

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Received: 2 July 2018

Abstract
The main aim of this study is to compare Russian regions according to their ability to create new technologies efficiently and to identify factors that determine these differences over a long period of time. We apply data envelopment analysis (DEA) to assess the relationship between the results of patenting and resources of a regional innovation system (RIS). Unlike previous studies, we apply the DEA method over a long period, comparing regions to one another and over time. In general, RIS efficiency in Russia increased during the period, especially in the least developed territories. There was significant regional differentiation. The most efficient RIS were formed in the largest agglomerations with leading universities and research centers: the cities Moscow and Saint Petersburg and the Novosibirsk, Voronezh, and Tomsk regions. Econometric calculations show that RIS efficiency was higher in technologically more developed regions with the oldest universities and larger patent stock. Time is a crucial factor for knowledge accumulation and creating links between innovative agents within RIS. Entrepreneurial activity was also a significant factor because it helps to convert ideas and research into inventions and new technologies and it enhances the interaction between innovative agents. It is advantageous to be located near major innovation centres because of more intensive interregional knowledge spillovers. Public support of more efficient regions can lead to a more productive regional innovation policy.

Keywords Patent activity · Regional innovation systems · Russian regions · Data envelopment analysis · DEA · R&D expenditures · Human capital

JEL Classification O30

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Published online: 07 June 2019

Introduction

In 2000, federal strategy declared innovation policy one of the imperatives of the socio-economic development in Russia (Perret 2014). At that time, the majority of the Russian regions had become wealthier in terms of gross regional product (GRP) per capita, driven largely by high global oil and gas prices. Fiscal reform was carried out, which made it possible to distribute oil and gas revenues among all the regions (Desai et al. 2005). However, economic growth based on the redistribution of oil rent between regions could not lead to innovative development by itself. The Dutch disease in poor institutional environment may have caused the simplification of the economy, creating less favorable conditions for new sectors and research and development (R&D) (Algieri 2011).

There were some contradictory trends in the development of the national innovation system. On the one hand, public spending on innovative activities was increasing and the Russian government created a significant number of policy instruments for promoting innovation (Zemtsov and Barinova 2016). Many new institutions appeared, such as Rusnano (established in 2007) and the Russian Venture Company (established in 2006), regional venture funds, and so on. A large variety of innovative infrastructure was created in the regions: special economic zones, technology parks, and technology transfer centers. On the other hand, the share of R&D expenditures in GDP remained stably low in comparison with developed countries (OECD 2018), while the share of R&D employment even declined (Perret 2014). A number of researchers have noted the presence of the Russian innovation paradox (Perret 2014; Crescenzi and Jaax 2017): limited success in translating scientific inventions into innovative products. In many Russian regions, their share of R&D costs in GRP is rather large, the share of people employed in R&D is even higher than in developed countries, but there is relatively little innovative activity, in other words, efficiency is low.

Despite the redistribution policy in Russia, there was still strong differentiation between the Russian regions in their innovation (Zemtsov et al. 2016). Although funding for innovative projects has increased, many regions reduced their patent activity dramatically compared with the Soviet period. The problems may be related to the efficiency of public R&D financing, infrastructure shortages, or insufficient regional human capital.

After the crises of 2008 and especially after 2014–2015, Russian economists and politicians were actively discussing directions for regional innovation policy in terms of the budget deficit (Zubarevich 2009; Zemtsov and Barinova 2016). Supporters of an equal distribution of resources between regions cite the need to equalize the level of socio-economic development. Other experts say that it is necessary to concentrate resources in the regions with the greatest potential, that is, those with the most efficient system of innovation support (Zemtsov and Barinova 2016; Zemtsov et al. 2016). To make political decisions about regional priorities of innovation policy, it is necessary to understand which regions are more efficient in creating new technologists and why.

Considering the above, the *aim of this work* was to compare the Russian regions by their ability to efficiently and effectively create new technologies. We further sought to identify the factors that determine these differences over a long period of time. Understanding these factors will help us improve regional innovation policy in Russia and it can be useful for other large developing countries. It was important for us to follow the dynamics of the regional efficiency to assess whether innovative activity was influenced by significant investments in the innovation sphere in the second half of 2000s and in which regions the return was the highest.

In accordance with this study's, we considered previous studies in detail and proposed a basic methodology for regional efficiency assessment. We offered a method based on data envelopment analysis (DEA). DEA is one of the most common non-parametric instruments used for measuring the efficiency of different decision making units such as banks, universities, enterprises, regions, and even countries. The DEA method in our case uses the tools of mathematical programming to plot the efficiency frontier on a sample of regions along the coordinates of the input and output variables describing innovation resources and results. The longer the distance to the efficiency frontier, the lower the efficiency score for a region (Murillo-Zamorano 2004; Kotsemir 2013). Our overview showed that DEA is a widespread method for analyzing the efficiency of regions in the innovation sphere. Lastly, based on the proposed econometric model, we tried to identify some efficiency factors to formulate key recommendations for regional policy.

The examples of the analysis of regional innovation systems in Russia with the DEA approach are found in the following works: (Didenko et al. 2011; Baburin and Zemtsov 2014; Didenko and Egorova 2014; Zemtsov and Baburin 2017; Rudskaia and Rodionov 2018). The novelty of our research lies in the fact that we run the RIS efficiency analysis over time. Further, we provide an illustrative visualization of RIS efficiency scores, their dynamics, and the patent commercialization potential of Russian regions on one map of Russia. Finally, we identify the factors of RIS efficiency by applying econometric analysis.

Theoretical and empirical background

In large countries, such as the US, Canada, Russia, China, and others, the level of innovative development between regions may differ significantly (Asheim and Gertler 2005). There are a few regions with high innovative activity. Most often this activity it is associated with the formation of an efficient regional innovation system (RIS), in which research is quickly turned into innovative products without extra labor and capital costs.

A regional innovation system (RIS) is a network of innovative agents including educational institutions, scientific organizations, businesses, and government agencies as well as the interactions between them within the scope of specific regional institutions and infrastructure (Cooke et al. 1997). RIS efficiency depends on accumulated knowledge, its human capital, R&D financing, and the ability of innovative agents to interact and create new technologies (Broekel et al. 2014).

Economic efficiency analysis is based on two types of methods: cost–benefit analysis and frontier techniques. The concept of cost-benefit analysis was formally proposed in Dupuit (1848), further formalised in works of Marshall (1890), Kaldor (1939), and Hicks (1939) (whose work is based on Pareto optimum conception (Pareto (1896)) and broadly introduced to the analysis of public sector in Eckstein (1958). Michael J. Farrell (Farrell 1957), influenced by Koopmans (1951) and Debreu (1951), was the first who decomposed the overall efficiency of the production unit into two components: technical and allocative efficiency. Later different methods of frontier analysis were developed. There are two groups of methods: parametric and non-parametric. In non-parametric methods the efficiency scores are accurately calculated on the basis on empirical (in the form of piecewise envelop) efficiency frontier built on observed objects of analysis. Parametric methods stochastically estimate the efficiency scores (Kotsemir 2013). Basic parametric frontier method of analysis is the method of stochastic frontier analysis (approach) (SFA), developed by Aigner et al. (1977). The key nonparametric method of frontier analysis is data envelopment analysis (DEA) approach (see Seiford 1996; Cook and Seiford 2009; Emrouznejad and Yang 2018 for a comprehensive overview of developmetnt of DEA method) developed by Charnes et al. (1978). In the framework or regional innovation systems DEA method can be applied to compare regions and identify the best of them.

In essence, DEA is a model based on mathematical programming, which is applied for the analysis of observed data for the construction of an efficiency frontier as well as for the calculation of efficiency scores based upon this frontier. For more information see (Murillo-Zamorano 2004). Consider the group of the N homogeneous objects of analysis (decision-making units—DMU), each of which is characterized by a vector of "*k*" input variables and "*l*" output variables. For each object of analysis that does not lie on the efficiency frontier, we can determine the vector $\lambda = (\lambda_1, \ldots, \lambda_N)$, where each λ_i represents the weight of each (*i*th) object of analysis in this set of reference (control, target) objects. The DEA model assesses the relationship between the results achieved by DMUs (that are measured by output variables) and available resources (measured by input variables): the higher the output is at lower costs/resources (i.e. input variables), the higher are the DEA scores. Key advantages and limitations of DEA method in application to the analysis of innovation system efficiency are summarized in Table 1.

In the case of regional innovation studies (Table 3 in an "Appendix"), the analysis of the European regions (primarily Germany) (Fritsch and Slavtchev 2006, 2007, 2011; Zabala-Iturriagagoitia et al. 2007; Broekel et al. 2013; Foddi and Usai 2013) and Chinese provinces (Chen and Guan 2012; Xu and Cheng 2013; Kaihua and Mingting 2014; Li et al. 2014; Liu et al. 2014) are the most widespread. Examples of RIS efficiency measurement for other countries can be found in Roman, 2010 (Romania and Bulgaria); Valdez Lafarga and Balderrama 2015 (Mexico); and Han et al. 2016 (Korea Republic). Chinese authors tend to use quite sophisticated DEA models: two-stage DEA models at the regional level (Xu and Cheng 2013; Kaihua and Mingting 2014); network and multi-period DEA models at the country (Guan and Zuo 2014; Kou et al. 2016) and regional levels (Chen and Guan 2012); the knowledge production DEA model (Liu et al. 2014); and the parallel DEA game model at the regional level (Zuo and Guan 2017).

Previous papers show that the DEA method very much depends upon the quality of the data. It is reasonable to remove observations of extremely low and extremely high values of the variables from the sample. The deletion of regional outliers from the sample helps reduce biases in the efficiency scores. The scope (size) of the regions should be taken into account. The smallest regions with the least number of researchers can be more efficient if we use a model with constant returns to scale.

For our purposes, it is important that in most previous studies *R&D expenditures* and *number of R&D personnel* were used as input variables while *patent activity* was used as an output variable[1] (Nasierowski and Arcelus 2003; Roman 2010; Broekel et al. 2013; Foddi and Usai 2013). Some authors take into account sales of new products as output in their models (Kaihua and Mingting 2014; Xu and Cheng 2013; Chen and Guan 2012).

We did not find a proper theoretical model to identify the main RIS efficiency factors, but there are several widely used determinants (Fritsch 2003a, b, 2004; Fritsch and Slavtchev 2011; Zabala-Iturriagagoitia et al. 2007).

[1] The use of normalized indicators may lead to a misinterpretation of the real relationships within the RIS and some relative variables cannot be higher than 100%, however, it is possible in the DEA model if it is a "desired" output. Therefore, it is more appropriate to use the absolute (or per capita) numbers.

Table 1 Advantages and limitations of the DEA method for measuring innovation system efficiency. *Source*: Based on analysis of Murillo-Zamorano (2004), Bonaccorsi and Daraio (2004) and Cooper, Seiford and Tone (2006) papers

DEA method advantages	Applications of these advantages to analysis of national (and regional) innovation systems efficiency
Efficiency scores as an integral index	Researchers and policymakers use objective aggregate in contrast to subjective aggregate score in the case of index method (weighing of different components in an index is subjective in any case)
No a priori hypothesis on the functional relationship between input and output variables	No influence recorded by the subjective choice of the functional form of the relationship between input and output variables on efficiency scores in contrast to stochastic frontier analysis method
No restrictions on the weights for input and output variables	No influence recorded by the subjective choice in weights of input and output variables on efficiency scores
Opportunity to include multiple output variables	All aspects of national innovation system performance can be accounted for by using several (instead of only one) output variables. No influence of the subjective choice/constructing of only one integral output variable recorded on efficiency scores as it is in Stochastic frontier analysis method
DEA method limitations	**Methods and theoretical developments for diminishing or eliminating these limitations**
High dependency of efficiency scores on outliers	This problem can be solved by using nonparametric frontier technique for efficiency analysis with the robust efficiency frontiers (Cazals et al. 2002). This method eliminates the influence of outliers upon efficiency scores
Efficiency scores are not cleared from statistical noise	This problem can be solved by using the Stochastic Nonparametric Envelopment of Data (StoNED) technique, which decomposes efficiency scores on random noise and inefficiency like SFA method. StoNED does not set any a priori hypothesis on the functional form of the relationship between input and output variables (Kuosmanen 2008). Some approaches to diminishing the influence of statistical noise on efficiency scores were proposed within the framework of non-parametric frontier techniques in the early 2000s (Hall and Simar 2002; Simar 2003)
Efficiency scores can be incorrect in models with a very small sample size and very large number of input and output variables	In 1990s and early 2000s, some techniques with small samples within DEA models were proposed: General analysis of sample size bias (Zhang and Bartels 1998) Robust order m efficiency frontiers techniques (Cazals et al. 2002) Method of parametric approximation of nonparametric techniques (Florens and Simar 2002) Slack-based measure of efficiency (Fare et al. 1994; Tone 2001)

The largest agglomerations have the highest concentration and diversification of all innovative agents (universities, firms, R&D-centers, etc.) and accordingly the intensity of interaction between them is higher (Audretsch 1998; Feldman 2000).[2] The proximity of firms can be beneficial in connection with the availability of access to specialized factors of production and to specific knowledge and competencies. The effects of urbanization are manifested with the high concentration (density) and diversification of agents. The formation of new technologies outside of cities is possible, but very limited.

Some regions may maintain a high level of innovative activity for decades despite changes in financing and other external factors (Feldman 1994). This can be achieved because of the following institutional factors (Broekel 2012), *the embeddedness of the regional innovation system*:

- the accumulation of information, knowledge and skills in innovative processes,
- the constant improvement of institutional structures to support innovative initiatives,
- the formation of networks for researchers, entrepreneurs, and other innovation agents;
- the creation of an environment of trust, openness to new ideas, and high prestige for innovators.

The embeddedness in this case occurs at the local and regional levels after many years of development because of the importance of tacit knowledge spillovers, which cannot be transferred over long distances because they imply direct interaction with their sources (individual specialists, a university, a company, a research think tank, and so on) (Feldman 2000; Boschma 2005; Aldieri et al. 2018). Tacit knowledge (Polanyi 1967) cannot be fully formalized and can be only transmitted "from teacher to student" through interactive learning. It is concentrated in areas where there are scientific schools, large research centres, and other types of infrastructure (Gertler et al. 2000). Knowledge has a cumulative nature; it takes time for an innovation to take root in social systems: the formation of agents' interaction networks, the creation of a cultural environment which is open to new ideas, and, finally, the cultivation of local community interest in innovations and the corresponding support institutions. The process of creating and implementing new technologies should be institutionalized according to a universal set of actions or "routines" in the terminology of R. Nelson (Nelson and Winter 1982).

The technological development of the region, its ability to create and use new knowledge depends upon the R&D intensity (Griliches 2007).

Another important feature of a significant part of knowledge as a public good is indivisibility, that is, the ability to use it an unlimited number of times and in various fields of activity. Therefore, the innovative activity of some agents generates positive externalities for others—*knowledge spillovers* (Aldieri et al. 2018). The returns from new knowledge at the level of regions and industries is significantly higher than at the level of a specific firm (Griliches 2007).

In addition, the potential for interaction is higher in regions with better institutions and developed entrepreneurship. In the model of Romer's production function (Romer 1986), economic growth through the R&D sector depends upon the stock of knowledge and human capital. Nevertheless, the European Union has accumulated a significant amount of scientific knowledge and a high level of human potential, but the return from R&D is lower than

[2] The closer are agents, the higher is the probability of their interaction. In this case, geographical proximity is an indicator of technological, institutional, and social proximity (Boschma 2005).

in the United States. This contradiction with the theoretical model has received the name of “the European innovation paradox” and its explanation was proposed in Audretsch and Keilbach (2004). It is related to low entrepreneurial activity in the European regions. The region itself is not a source of innovations, new ideas, technologies, and products with firms acting as the main institutional form. The firm is one of the most important innovative agents participating in the creation and dissemination of new knowledge and technologies. Total factor productivity is not influenced by scientific and technological potential itself, but only in conjunction with start-up activity (so-called entrepreneurial capital) (Audretsch and Keilbach 2004). The emergence of new firms is a kind of transfer mechanism when new technologies are implemented at start-ups, allowing for the commercialization of ideas, scientific, and research capacity. Interaction between firms and other innovation agents is an important factor of RIS efficiency (Fritsch 2004; Staníčková and Skokan 2011).

According to Fritsch and Slavtchev (2011), the level of *specialization* can be an indicator of potential cluster formation. The effects of clustering arise from the joint localization of enterprises in a general field of activity (Porter 1998). Cluster members constantly interact and adopt the latest developments from one another. The intensity of interaction between innovative agents in clusters is higher and, accordingly, the RIS efficiency of highly specialized regions is high.

In Russia which regional innovation policy is needed is the subject of frequent discussion (Zubarevich 2009; Zemtsov and Barinova 2016). Some experts believe that the location of supported projects and start-ups does not matter. The studies described above demonstrate that it is more efficient to support projects and create research centers in regions with large agglomerations, established research schools, and a high level of technological development or close to them. In large agglomerations, labor productivity in the R&D sector and high-tech industries is higher due to the presence of a large market for new goods, services, personnel, and technology, the availability of venture capital, and the high intensity of interaction between agents (Dmitriev et al. 2018). The implementation of new projects requires a large set of interrelated competencies that can only be obtained in the long-established regional innovation systems with a high intensity of interaction between innovation agents.

Accordingly, we formulate five hypotheses of the research.

H1 The largest agglomerations are more efficient in new technology creation because of the higher concentration and interaction between innovation agents.

H2 The RIS must be embedded to create new technologies efficiently. If the RIS is young, does not have sufficient knowledge stock, it is less efficient.

H3 Regions with a high level of technological development are more efficient. In other words, the high intensity of R&D expenditures contributes to an increase in the efficiency of RIS.

H4 The nearest regions to the largest innovation centers are more efficient because it is easier for them to accept tacit knowledge through knowledge spillovers.

H5 The regions with a better institutional environment for entrepreneurship create better conditions for the interaction between innovative agents, and, accordingly. RIS efficiency is higher in these regions.

Data and methodology

We use the data envelopment analysis (DEA) technique to assess the regional innovation system efficiency. For the DEA approach, we had to identify suitable output and input variables. We based our estimations on one of the most widely used conceptual models—the knowledge production function (KPF). The KPF sets out the relationships between R&D spending, human capital, and innovation (Griliches 2007; Zemtsov et al. 2016).

According to Romer (1986), new knowledge is produced as a result of using concentrated human capital and the existing stock of knowledge. Griliches (2007) defined a knowledge production function based on the simple concept of 'inputs-outputs'. He showed that R&D expenditures influence the production of certain unobservable knowledge that has economic value. Yet only some of this knowledge can be identified and measured. The production of knowledge is determined by current R&D expenditures in the region, by previous expenditures (cumulative), and by R&D expenditures in neighboring regions (knowledge spillovers) (Griliches 2007). However, unlike deterministic production processes, the creation of new technology has a probabilistic nature. It is impossible to increase the generation of new technologies only by increasing financing, since the process is cumulative with a large share of tacit knowledge. Alternative models indicate that human capital and entrepreneurial activity are more important factors for patent activity (Brenner and Broekel 2011; Crescenzi and Jaax 2017).

A common, yet often criticized, indicator of *innovation output* is the number of patents, which have been used for many decades (Griliches 2007; Zabala-Iturriagagoitia et al. 2007; Fritsch and Slavtchev 2011). Yet we should remember that although patents can be considered a result of inventions, not all patents will be commercialized and be realized as an innovative product or process. About 64% of national patents in the largest European countries (France, Germany, Italy, Netherlands, Spain, and the UK) are commercialized (Gambardella et al. 2007) while 55% of triadic patents in the USA are commercialized (Walsh et al. 2016) and 52.4% of patents in China.[3] Unfortunately, Russian regions on average have a low share of commercialized national patents: in the 2000s, this did not exceed 8% (Zemtsov et al. 2016). Another indication of the low quality of patents in the Russian regions is the high volatility in the number of patent applications over time and the excessively high number of patents per capita in some regions. For example, the Ivanovo region (15 in Fig. 2) had a surprisingly high increase in the number of the Russian patent applications: about 13 times in just 2 years from 2006 to 2008 without any corresponding increase in R&D funding or the number of researchers (Baburin and Zemtsov 2013). One author, Julia Schepochkina, was involved in more than 1000 patents for inventions. Patents are registered as a form of reporting for research and development. Their registration is free for individuals. Regional patent offices are simply not able to assess their real scientific or commercial value. If the number of patents becomes an indicator of the quality of the work of researchers, their number increases dramatically with a corresponding decrease in quality. In Russia, there is a similar situation to that in China (Dang and Motohashi 2015).

Applying for an international Patent Cooperation Treaty (PCT) patent is generally considered much harder than for a Russian national patent because the verification process and registration can take several years while the costs at different stages of the process can add

[3] NTD intellectual property newsletter. URL: https://docplayer.net/27207042-Ntd-intellectual-property.html.

up to \$3000 (WIPO 2017). The major benefit however is that PCT patents have a greater degree of commercialization. About 42% of PCT patents are in force around the world after 7 years (WIPO 2017), which means they are still used. However, a significant drawback of using PCT patent statistics are the very low levels of patenting in most Russian regions (Zemtsov et al. 2016).

We collected data from the Russian statistical service (if not mentioned otherwise) for the period 1998–2012.[4]

We cannot use the indicator of national patents due to the low quality of these patents in some regions, so we developed a complex indicator that takes into account Russian and international patents. We cannot simply summarize the two indicators due to differences in their quality and commercial use. That is why we took national and international patents with an assessment of their potential commercialization. This assessment helps to understand how patents really can be used later to create new technologies. Unfortunately, we only have averaged data for Russia, so the level of commercialization will be the same for all regions, although the regions (for example, Ivanovo region) may vary greatly. However, the use of this indicator, in our opinion, has significant advantages in comparison with individual values on Russian and international patents in terms of evaluating the innovative output (1). The indicator can be used as proxy for the new technology.

$$\mathrm{Innov}_{i,t} = 0.08 \times \alpha \times Pat\_rus_{i,t} \times \mathrm{Reg}_{i,t} + 0.5 \times \mathrm{PCT}_{i,t}, \tag{1}$$

where *i*—region, *t*—year, *Pat_rus* is the number of submitted patent applications registered by agencies of the Federal Service for Intellectual Property (Rospatent); *Reg* is an average share of registered patent application in previous 3 years, PCT is the number of submitted PCT patent applications.[5] The coefficients here reflect the rate of commercialization for each type of patents.

Most of the patents are concentrated in the regions with the largest agglomerations (more than 1 million citizens in 2012): Moscow city—664 patents and Moscow Region—157 patents; Saint Petersburg—146; Republic of Tatarstan—59; Samara Region—45; Sverdlovsk Region—40; Rostov Region—37; Novosibirsk Region—35; Nizhniy Novgorod Region—35 (Fig. 1). However, there are some regions with less than one potentially commercialized patent: Nenets and Chukotka autonomous districts, the Republic of Kalmykia, the Republic of Ingushetia, the Republic of Altai, and so on. They are the least developed Russian regions.

In accordance with the knowledge production function (Romer 1986; Griliches 2007) and previous regional studies (Zemtsov et al. 2016; Crescenzi and Jaax 2017; Nasierowski and Arcelus 2003; Roman 2010; Broekel et al. 2013; Foddi and Usai 2013) for the evaluation of RIS efficiency, two main resources must be taken into account: human capital involved in the creation of new technologies and R&D expenditures as a proxy for financial resources (see "Appendix", Table 3).

The *input parameters* of our model are real domestic expenditure on R&D in prices from 1998, million roubles, and the number of employed urban citizens with higher education, thousand persons (Zemtsov et al. 2016).

We calculate the indicator of human capital using the following formula (2):

$$\mathrm{HC}_{i,t} = Urb_{i,t} \times High\_empl_{i,t}, \tag{2}$$

[4] Russian regions. Socio-economic indictors. URL: https://www.fedstat.ru/indicator/39279.

[5] OECD. Database. URL: http://stats.oecd.org/Index.aspx?DatasetCode=PATS_REGION.

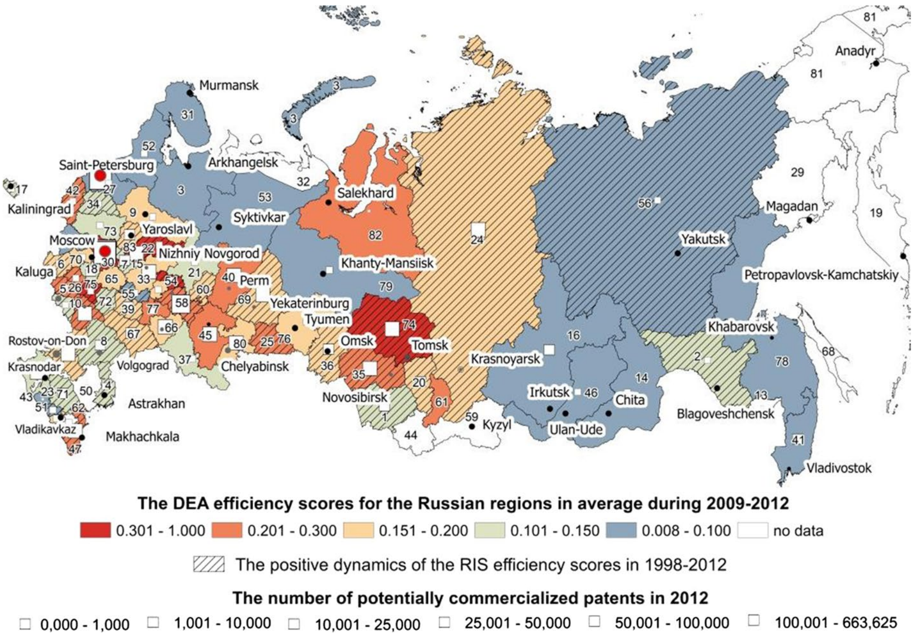

Fig. 1 The average RIS efficiency scores in 2009–2012. *Note*: number on the map shows the following regions; 1—Altai Krai; 2—Amur Region; 3—Arkhangelsk Region; 4—Astrakhan Region; 5—Belgorod Region; 6—Bryansk Region; 7—Vladimir Region; 8—Volgograd Region; 9—Vologda Region; 10—Voronezh Region; 11—Moscow Region; 12—Saint-Petersburg; 13—Jewish Autonomous Region; 14—Zabaykalsky Krai; 15—Ivanovo Region; 16—Irkutsk Region; 17—Kaliningrad Region; 18—Kaluga Region; 19—Kamchatka Krai; 20—Kemerovo Region; 21—Kirov Region; 22—Kostroma Region; 23—Krasnodar Krai; 24—Krasnoyarsk Krai; 25—Kurgan Region; 26—Kursk Region; 27—Leningrad Region; 28—Lipetsk Region; 29—Magadan Region; 30—Moscow city and Moscow Region; 31—Murmansk Region; 32—Nenets Autonomous District; 33—Nizhniy Novgorod Region; 34—Novgorod Region; 35—Novosibirsk Region; 36—Omsk Region; 37—Orenburg Region; 38—Oryol Region; 39—Penza Region; 40—Perm Krai; 41—Primorsky Krai; 42—Pskov Region; 43—Republic of Adygea; 44—Republic of Altai; 45—Republic of Bashkortostan; 46—Republic of Buryatia; 47—Republic of Dagestan; 48—Republic of Ingushetia; 49—Kabardino-Balkar Republic; 50—Republic of Kalmykia; 51—Karachai-Cherkess Republic; 52—Republic of Karelia; 53—Komi Republic; 54—Republic of Mari El; 55—Republic of Mordovia; 56—Republic of Sakha (Yakutia); 57—Republic of North Ossetia-Alania; 58—Republic of Tatarstan; 59—Republic of Tyva; 60—Udmurt Republic; 61—Republic of Khakassia; 62—Chechen Republic; 63—Chuvash Republic; 64—Rostov Region; 65—Ryazan Region; 66—Samara Region; 67—Saratov Region; 68—Sakhalin Region; 69—Sverdlovsk Region; 70—Smolensk Region; 71—Stavropol Krai; 72—Tambov Region; 73—Tver Region; 74—Tomsk Region; 75—Tula Region; 76—Tyumen Region; 77—Ulyanovsk Region; 78—Khabarovsk Krai; 79—Khanty-Mansi Autonomous District; 80—Chelyabinsk Region; 81—Chukotka Autonomous District; 82—Yamalo-Nenets Autonomous District; 83—Yaroslavl Region

where[6] *i*—region, *t*—year, *Urb*—the number of urban residents, thousand people; *High_empl*—the proportion of employees with a higher education (%).

We used the DEA method with decreasing returns to scale, the input-oriented model with technical efficiency. We do not estimate efficiency scores for each year of the research,

[6] The indicator (HC) takes into account the most likely generators of innovation—people who have sufficient knowledge, qualification, and infrastructure to carry out research on a permanent basis. We do not use the number of researchers (Crescenzi and Jaax 2017) because many urban residents with higher education (not only researchers) tend to produce new technologies, so it is more valid for our purposes (Zemtsov et al. 2016).

but do it for the whole period for comparability reasons. It was important to understand the dynamics of efficiency in this period, whether the innovative activity was influenced by significant investments in the innovation sphere in the second half of 2000s, and in which regions the return was highest, for example, whether Moscow or Tambov region became more efficient in 2009 in comparison with 1998. We excluded from our calculations Chechen Republic because of the lack of the data and some years for several other regions because of omissions in data and extremely high or low values (see "Appendix", Table 4).

We propose an empirical model to test five hypotheses of the research (3):

$$\begin{aligned} RISeff_{i,t} &= const + \ln City_{i,t} + \ln Embedd + \ln TechDev_{i,t} \\ &\quad + Know\_spill_{i,t} + RIS\_ineract_{i,t} + Special_{i,t} \end{aligned} \tag{3}$$

where *i*—region; *t*—year; *City*—indicators of agglomeration (population of regional centers) (to test hypothesis H1); *Embedd*—indicators of RIS embeddedness (age of the oldest universities, patent stock) (to test hypothesis H2); *TechDev*—indicators of technological development (R&D expenditures per GRP) (to test hypothesis H3); *Know_Spill*—indicators of interregional knowledge spillovers (potential for bilateral R&D cooperation; distance to the largest agglomerations) (to test hypothesis H4); *RIS_ineract*—indicators of the institutional environment and interaction between innovative agents in RIS (entrepreneurial activity) (to test hypothesis H5); *Special*—regional industrial specialization (share of processing industry in GRP).

We used an indicator for the number of citizens in the regional center as a proxy for agglomeration effects. In Russia, the innovation potential is almost exclusively concentrated in the regional center: the larger it is, the higher the concentration of innovative agents, the higher the intensity of their interaction, and, accordingly, the efficiency of creating new technologies (Audretsch 1998; Feldman 2000).

We used the age of the oldest universities[7] and the number of previous patents as a proxy for innovation embeddedness. The older is the first university, the larger is the stock of knowledge and patents that can be used for new technology creation (Romer 1986). To measure patent stock, we calculated a cumulative number of registered Russian patents from 1994. This indicator shows the volume of collected (and created) knowledge in the regions.

R&D expenditures per GRP[8] (Fritsch and Slavtchev 2011) was used as a proxy for it. The higher is the share of R&D in GRP, the more developed, more technologically improved innovation systems can be.

To measure potential knowledge spillovers related to interactions between researchers from different regions of Russia, we developed an indicator *Know_spill* that shows the potential for bilateral cooperation based on gravity models (Zemtsov et al. 2016). The higher is the indicator, the more potential interactions between researchers there could be (4).

$$Know_{spill_i} = \sum_j \frac{\sqrt{RnD_{empl_i} \times RnD_{empl_j}}}{R_{ij}^{\alpha}} \tag{4}$$

[7] We collected data from the official websites of the Russian universities.

[8] According to data of the Russian statistical service. Russian regions. Socio-economic indictors. URL: http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/publications/catalog/doc_1138623506156.

where RnD_{empl_i}—number of R&D staff of region i; RnD_{empl_j}—number of employees in regions j, located at a distance of R_{ij}[9] ; α—the coefficient, which is a measure of the extent to which the geographical distance reduces interactions among researchers.

Another indicator, distance to the largest agglomerations, was also used as a proxy for knowledge spillovers from the largest cities.

We used entrepreneurial activity (number of small firms per economically active population)[10] and start-up activity (the number of new high-technology firms per number of urban citizens with higher education)[11] as proxy for possible knowledge transfer mechanism and interaction of innovative agents. The higher is the number of firms and start-ups per capita, the higher is probability of their interaction. Our indicator is a proxy for entrepreneurial capital (Audretsch and Keilbach 2004). The higher is the above indicator, the greater is the number of people associated with business activities who have the appropriate competence to create firms and transform new ideas into personalized products and services.

We assumed that regions specializing in the manufacturing industry can be more efficient in creating new technologies according to Fritsch and Slavtchev (2011). We used the share of the manufacturing industry in GRP as an indicator.[12]

Results

In support of our first hypothesis (H1), the average RIS efficiency leaders over the whole period are mostly regions with the largest agglomerations: Moscow city, Tomsk region, Saint-Petersburg, Moscow region, Voronezh region, and the Novosibirsk region (Table 4 in the "Appendix"). We also estimated average efficiency scores for the post-crisis period 2009–2012 for comparison reasons (Fig. 1). The leaders did not change dramatically. However, many 'small' regions such as the Ivanovo region, Lipetsk region, and Kostroma region are also efficient.

The efficiency scores of the Russian regions were quite different during the period of 1998–2012. Only Moscow city was a stable leader. This may be because the creation of new technologies is a probabilistic process and if the concentration of human capital and R&D expenditures remain relatively stable, the number of patents can vary significantly.

To verify the hypothesis of more efficient agglomerations (H1), we divided all the regions in four groups according to the number of citizens in the regional center[13]:

[9] We measured the distance by the length of railway tracks between the regional capital cities. Where there was no railway line, we used the length of highways, and occasionally we used the length of rivers.

[10] We calculated the indicator according to data of the Russian statistical service. Russian regions. Socioeconomic indictors. URL: http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/publications/catalog/doc_1138623506156.

[11] We calculated the indicator using data from RUSLANA. URL: https://ruslana.bvdep.com/version-2017106/home.serv?product=Ruslana.

[12] We calculated the indicator according to data of the Russian statistical service. Russian regions. Socioeconomic indictors. URL: http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/publications/catalog/doc_1138623506156.

[13] According to data of the Russian statistical service. Russian regions. Socioeconomic indicators of cities. URL: http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/publications/catalog/doc_1138631758656.

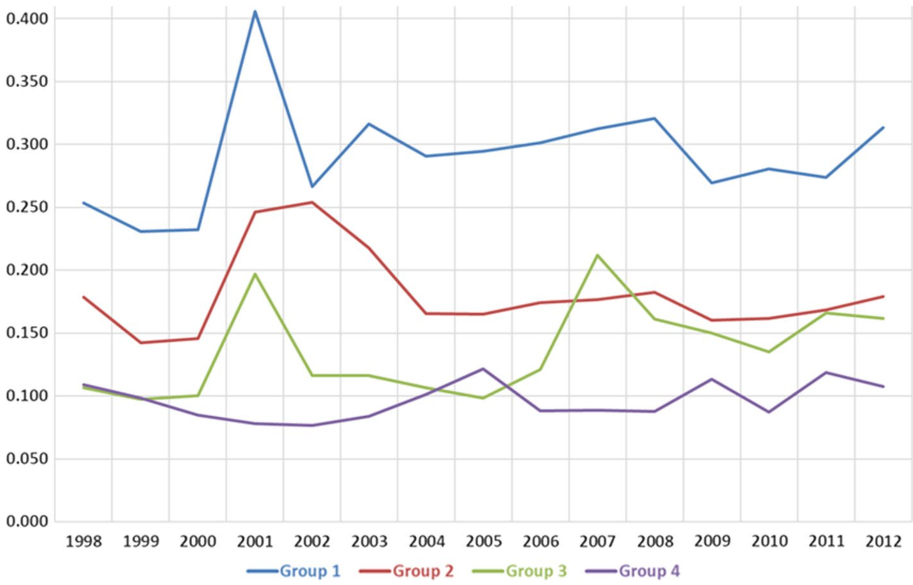

Fig. 2 The average RIS efficiency scores in Each Regional Group

- Group 1—the number of citizens in regional capitals is more than 1 million (the largest Russian agglomerations with developed scientific centers and the leading universities): the cities of Moscow and Saint-Petersburg, Leningrad region, Moscow region, Krasnoyarsk Krai, Novosibirsk region, Omsk region, Perm Krai, Volgograd region, and Tatarstan Republic.
- Group 2—the number of citizens in regional capitals is more than 500,000 but less than 1 million (large cities): Krasnodar Krai, Primorsky Krai, Khabarovsk Krai, Yaroslavl region, Tomsk region, Tyumen region, Irkutsk region, Astrakhan region, and Altai Krai.
- Group 3—the number of citizens in regional capitals is more than 250,000 but less than 500,000 (mid-sized cities): Kaluga region, Kaliningrad region, Murmansk region, Vladimir region, Belgorod region, Arkhangelsk region, Kursk region, Smolensk region, Stavropol Krai, Tver region, Ivanovo region, Tambov region, and Republic of Mordovia.
- Group 4—the number of citizens in regional capitals is less than 250,000 (small cities): Jewish autonomous region, Nenets autonomous district, Khanti-Mansiysk autonomous district, Yamalo-Nenets autonomous district, Sakhalin region, Novgorod region, Amur region, and Magadan region.

We compared the average DEA scores between these four groups (Fig. 2).

As one can see, during 1998–2005 the RIS efficiency obeyed a simple pattern: the larger the capital of the region, the higher is the average DEA efficiency score. After a sharp increase in energy prices, the efficiency of groups with small cities increased significantly: Khanti-Mansiysk, Yamalo-Nenets, and Nenets autonomous districts and the Sakhalin region are among the main Russian oil and gas centers. Only a group of regions with more than 1 million citizens in the central city (the first group) retained their leadership. The identified patterns can serve to partially confirm the first hypothesis (H1). At the next stage,

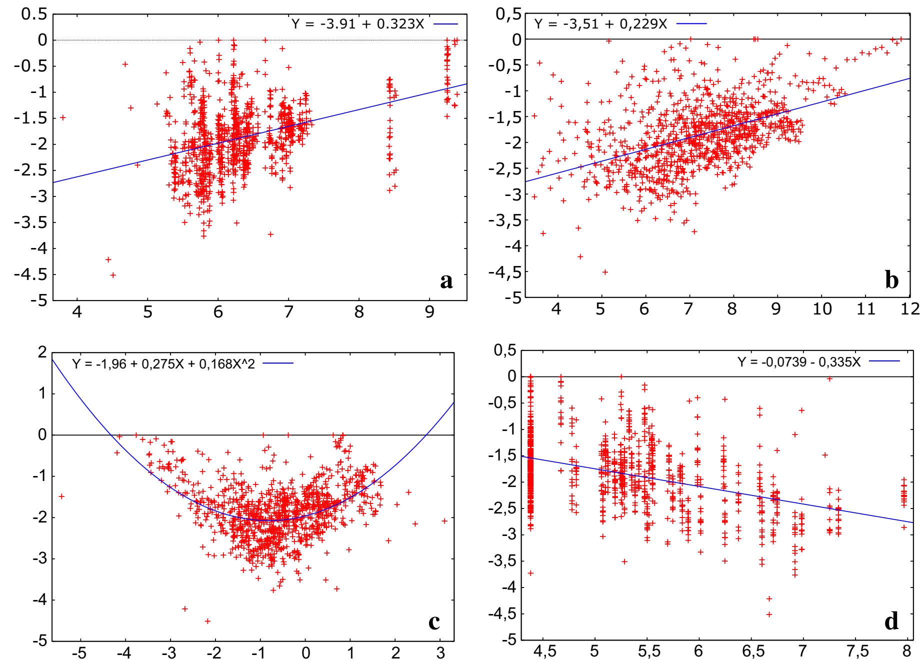

Fig. 3 Relationship between the Size of Population in the Regional Centers and **a** Patent Stock, **b** Distance to Agglomerations, **c** R&D Expenditures in GRP, **d** and RIS Efficiency Scores (vertical axis)

we sought to track the relationship between RIS efficiency and a number of previously described factors using scatterplots. All the variables were log-transformed (Fig. 3a–d).

It is not clear whether or not there is a positive relationship between the number of regional capital citizens and the DEA scores (Fig. 3a) because of high heterogeneity.

However, there is a positive correlation between patent stock (Fig. 3b) and RIS efficiency scores which can serve to partially confirm the second hypothesis (H2). Time is a crucial factor for knowledge accumulation and creating links between innovative agents.

We found that the ratio of R&D expenditures to GRP and RIS efficiency scores has a parabolic relationship (Fig. 3c): efficiency is higher in regions with a high and a low share of R&D expenditures in GRP. Regions with low R&D intensity can be quite efficient because patents can be a result of the pure creativity of people and not connected to systematic work of research institutions. More importantly, regions with high R&D intensity are still among the most efficient, which confirms the third hypothesis (H3).

The indicator of distance to agglomerations (Fig. 3d) is positively correlated with efficiency scores but we should take into account high heterogeneity. Most of the Russian agglomerations are large scientific and industrial centers. It is advantageous to be located near major innovation centers as this contributes to an increase in interregional knowledge spillovers due to the more intensive interactions between researchers and provides opportunities to use the scientific infrastructure of a major center (Zemtsov and Baburin 2016). The result can be used as an additional argument in support of confirming the fourth hypothesis (H4).

We calculated several models for spatial and panel data. In the first case, we sought to assess the factors that determine the regional heterogeneity of DEA efficiency scores. In the second case, we tried to assess the long-term factors of RIS efficiency. We chose the final models with significant variables according to the highest R^2 and the lowest Akaike information criterion (Table 2). The variables were checked for multicorrelation.

The most important and significant factors of RIS efficiency in Russia in the long term (1998–2012) are regional patent stock, R&D intensity, and entrepreneurial activity. It is impossible to create an efficient RIS in the short term because it is essential to accumulate knowledge and form links between innovation agents.

Despite the fact that the regions with the largest agglomerations are more efficient in new technology creation, as we demonstrated (Fig. 2), we did not choose the final models with this indicator because they had less explanatory power. We also cannot put the indicator in chosen regressions because of multicollinearity problems: it is highly correlated with the age of the oldest university, with high entrepreneurial activity, and the knowledge (patent) stock.

Our results show that the older is the first university in the regions, the larger is the knowledge stock and higher the modern RIS efficiency. If the cumulative sum of previous patents in the region is higher by 1%, its RIS efficiency is higher by 1.3% than other regions. It is much easier to attract new scientists and to create new technology when there is a great scientific and cultural heritage. The most prestigious Russian universities were established before the twentieth century or in the first half of the century: Moscow, Saint Petersburg, Tomsk, Kazan, and Samara universities. Further, many young universities were created in small regional centers in the 1990s, when the educational standards dropped. Some of the old universities have become national research universities with modern scientific programs while the younger institutions cannot afford research expenditures and only perform educational functions. The age of the university is a proxy for the number of years higher education and research have been performed in a region. The oldest universities have already established a creative environment in the region, interacting with scientific organizations, other firms, and creating start-ups. So, they formed a regional innovation system.

We also confirmed a parabolic relationship between the ratio of R&D intensity and RIS efficiency (Fig. 3c). At the same time, the linear dependence is negative: if the government increases R&D intensity in all regions by 1%, it will lead to decrease in efficiency scores by 0.13%. This is attributable to the fact that in some regions with high R&D intensity, there are many non-technical research organizations specialized on basic research (Russian Academy of Science), which do not produce patents but only scientific papers.

It is also important to be located near a big scientific center for interregional knowledge transfer. According to our calculations, entrepreneurial and start-up activities are significant factors of RIS efficiency (Table 2).

An increase in entrepreneurial activities by 1% will lead to an increase in the efficiency scores by 0.25%. From our point of view, entrepreneurial activity helps convert ideas and research studies into inventions and new technologies (Audretsch and Keilbach 2004). Many regions around Moscow with high RIS efficiency scores (Fig. 1) are also highly specialized in the manufacturing industry. If the share of the manufacturing industry is 1% higher in the region, its RIS efficiency is 0.12% higher.

Table 2 Regression results for RIS efficiency factor identification

Dependent variable: ln(the RIS efficiency scores). 978 observations, 72 regions, 1998–2012

Factor of RIS efficiency	Variables	Coefficient (Std. Error)		
		Pooled OLS model		Fixed-effects model. Time dummies included
Embeddedness	Ln (the oldest university age)	0.29*** (0.07)	0.19*** (0.07)	
	Ln (the Russian national Patents' stock)		0.15*** (0.03)	1.3*** (0.07)
Technological development	Ln (R&D expenditures per GRP)	0.02 (0.06)	0.02 (0.06)	−0.14*** (0.02)
	Ln (R&D expenditures per GRP)^2	0.13*** (0.02)	0.13*** (0.02)	0.13*** (0.01)
Knowledge spillovers	Ln (potential interregional knowledge spillovers)	0.11*** (0.04)	0.11*** (0.03)	
	Ln (distance to agglomeration with more than 1 mln. of residents)	−0.23*** (0.05)	−0.15*** (0.05)	
RIS inner interactions	Ln (number of small enterprises per economically active population)			0.15*** (0.05)
	Ln (number of high-technology start-ups per number of urban citizens with higher education)	0.25*** (0.08)		0.1*** (0.03)
Industrial specialization	Ln(share of the processing industry in GRP)			0.12** (0.05)
	Constant	−2.2*** (0.38)	−3.17*** (0.38)	−9*** (0.41)
Model quality criteria	*R*-squared	0.48	0.54	
	Adjusted *R*-squared	0.48	0.54	
	LSDV *R*-squared			0.85
	Within *R*-squared			0.52

***p value significance is lower than 0.01 (1%); **p value significance is lower than 0.05 (5%). See Table 5 for the data sources of all variables

Conclusion

We proposed a basic methodology for the assessment of regional efficiency in Russia, comparing the results of patenting (creating new technologies) with the human and financial resources of an innovation system.

We confirmed the group of regions with the largest agglomerations (Moscow, Saint Petersburg, Novosibirsk, Tomsk, etc.) are the efficiency leaders because they possess the largest and the oldest universities and demonstrate higher R&D intensity and are home to many technological entrepreneurs. That is why we can consider the first hypothesis (H1) generally confirmed. Priority public support of more efficient regions, including large agglomerations, may lead to a more productive regional innovation policy in Russia. However, the presence of the largest agglomeration itself is not as important for RIS efficiency as the knowledge stock associated with it. It is impossible to create an efficient RIS in the short term because it is essential to accumulate knowledge and form links between innovation agents. We also consider the second hypothesis (H2) confirmed: if the RIS is young and does not have sufficient knowledge stock, it is less efficient and may not be the primary target of innovation policy.

At the same time, the least developed regions (most of the agrarian and raw material centers) are less efficient in patent creation because of the lack of research institutions, human capital, and knowledge. It is important to mention that some 'small' (in terms of economy size) regions such as the Ivanovo, Lipetsk, and Kostroma regions are quite efficient in terms of patent creation. These regions are mostly specialized in the manufacturing industry, technical education is well developed, and synthetic and analytical types of knowledge prevail (Tödtling and Trippl 2005). As a result, patents are a widely used result of intellectual activity.

We found fluctuating dynamics of efficiency scores for most of the regions. In general, there is no noticeable growth or decline. After 2005, the convergence of regions began and the least efficient regions raised their scores. This may be explained by the success of equalizing regional innovation policy (Zemtsov and Barinova 2016; Zemtsov and Tsareva 2018).

We further found that the ratio of R&D expenditures to GRP and RIS efficiency has a parabolic (U-shaped) relationship (Fig. 3c): the efficiency scores are higher in the regions with high and low shares of R&D expenditures. Regions with a low R&D intensity can be quite efficient because patents can be the result of pure creativity unrelated to the work of research institutions with larger funds and a great number of employees. It can be also a result of decreasing returns of scale in innovation: the smallest specialized centers may be more efficient than larger centers with diversified interests, higher variety of facilities, and more complex interactions. More importantly, regions with a high R&D intensity are still among the most efficient, which confirms the third hypothesis (H3). At the same time, the linear increase in R&D funding intensity itself by 1% is associated with a decrease in scores by 0.13%. In other words, if the government equally increases R&D support in all regions ("spreads butter over the bread") it may cause decrease in the overall efficiency in comparison with a more focused innovation policy. From our point of view, it is more efficient to prioritize public innovation support (public venture funds, innovation infrastructure, commercialization centers, etc.) on the technological leaders with the highest R&D intensity. For lagging regions, it is possible to implement other forms of support as a part of social or entrepreneurial policy.

The distance to agglomerations is a significant factor in the differentiation of the RIS efficiency scores. It is a proxy for access to scientific and educational centers: many “small” (in terms of economy) regions (such as the Kostroma, Lipetsk, and Vladimir region,) can use Moscow research results to create new technologies (interregional knowledge spillovers). That is why the fourth hypothesis (H4) is correct: it is less efficient to support and implement large innovative projects far away from the largest innovation centers because this makes it difficult to accumulate tacit knowledge through knowledge spillovers.

In this work, we assessed the internal interactions of regional innovation systems indirectly—through entrepreneurial activity. We assumed that a higher number of firms leads to a higher probability of interaction. Our calculations show that the higher the entrepreneurial and start-up activities are, the higher are RIS efficiency scores. Confirming the fifth hypothesis (H5), we believe that the regions with a better institutional environment for entrepreneurship creates better conditions for interaction between innovative agents and that start-ups can be considered a spillover mechanism for translating ideas and research results into patents and new technologies.

Our results show that it is less efficient to support new technology development in all regions simultaneously and equally. In remote and technologically underdeveloped regions, RIS efficiency is lower than in large agglomerations and manufacturing centers with high R&D intensity, accumulated knowledge, and entrepreneurial activity. Although it may seem obvious that a “one size fits all” innovation policy is not applicable at a regional level (Tödtling and Trippl 2005), adepts of the equal distribution policy refer to the need to equalize the level of socioeconomic development. From our point of view, the support of leaders and smart specialization is more efficient and suitable innovation policy for Russia (Zemtsov and Barinova 2016).

It is important to note for further research that we explored regional efficiency only in terms of new technology creation. However, in some papers (see “Appendix” Table 3), the authors also evaluated the ability to create high-tech products and export them. Unfortunately, there was no such data for the whole period in Russia. We hope that it will be possible in the future to assess the influence of innovation infrastructure, venture investment, and other factors on RIS efficiency.

Acknowledgements The research leading to these results was supported by the Ministry of Science and Higher Education of the Russian Federation (Project ID: RFMEFI60217X0021). The authors are grateful to Vera Barinova from the Gaidar Institute for Economic Policy for valuable comments.

Appendix

See Tables 3, 4, and 5.

Table 3 Description of some studies on innovation system efficiency with DEA method

Publication year and authors(s)	Input variables (in authors' terminology)			Output variables (in authors' terminology)				DEA model used; number of countries/regions; years of analysis
	Human Capital	R&D and education expenditures	Other input variables	Patents	Publications	High-technology sector	Other output variables	
National innovation systems								
Rousseau and Rousseau (1997)	Active population	R&D and education expenditure	…	Patents granted by the EPO	Publications in the SCI	…	…	CRS OO; 18 (14 EU countries, plus USA, japan, Canada, Australia); 1993
Rousseau and Rousseau (1998)	Active population	R&D expenditure	…	Patents granted by the EPO	Publications in the SCI	…	…	CRS OO; 18 (14 EU countries, plus USA, japan, Canada, Australia); 1993
Nasierowski and Arcelus (2003)	Employment in R&D	R&D and education expenditure	Import; private R&D	Patents	…	…	National productivity	CRS OO; 45 (all over the world); 1993 and 1997
Lee and Park (2005)	Average researchers	Average R&D expenditure	…	Triadic patent families in 1999	Scientific and technical articles	Technology balance of receipts in 1999	…	CRS OO; 27 (all over the world); 1994–1998 (inputs) and 1999 (outputs)
Meng et al. (2006)	Full-time research staff	Investment	…	…	SCI publications	…	Total citations, and postgraduate enrolments of science	IRS IO; China; 1991–2000, years as DMUs
Sharma and Thomas (2008)	Researchers per million population	R&D expenditure	GDP; population	Patents granted to residents	Publications	…	…	VRS IO; CRS IO; 22 (all over the world) 2002 (inputs) and 2004 (outputs)

Table 3 (continued)

Publication year and authors(s)	Input variables (in authors' terminology)			Output variables (in authors' terminology)				DEA model used; number of countries/regions; years of analysis
	Human Capital	R&D and education expenditures	Other input variables	Patents	Publications	High-technology sector	Other output variables	
Cullmann et al. (2009)	Researchers	Different types of R&D expenditure	…	…	Weighted and unweighted patents.	…	…	VRS OO; 28 (all over the world); 1995–2004
Hung et al. (2009)	Full-time equivalent researchers	R&D expenditure	…	…	Weighted share of the world's publications	…	…	VRS OO; 27 (all over the world); 1993
Abbasi et al. (2011)	Scientists in R&D	Expenditure on education and R&D	…	Patent counts		High-tech and manufacturing exports	Royalty incomes	Based on VRS OO; 44 (all over the world); 2003
Pan et al. (2010)	R&D personnel	Public educ. And R&D expenditure	Imports; direct investment stocks abroad	Patents	Scientific articles	…	…	VRS IO; Super-efficiency model; 33 (Asia and Europe); 2004 and 2006
Hudec and Procházková (2013)	Scientists and researchers	Private and public R&D expenditures	Labour, knowledge stock	Patents	International scientific papers	Export of new high-tech products	Added value of industries	VRS IO and VRS OO; 19 (EU countries); 2004–2010
Guan and Zuo (2014)	Full-time equivalent researchers	Gross domestic expenditure on R&D	Full-time equivalent of non-R&D labor	…	Publication in scientific journals	Export in high-tech industries	Added value of industries (AVI)	Dual network-DEA models; 35 countries (all over the world); 2007–2011
Lu et al. (2014)	R&D personnel	Educational and R&D expenditure	Import (ICGS)	Patents	Published scientific articles	…	…	Two stage model; 30 (all over the world); 2007–2009

Table 3 (continued)

Publication year and authors(s)	Input variables (in authors' terminology)			Output variables (in authors' terminology)				DEA model used; number of countries/regions; years of analysis
	Human Capital	R&D and education expenditures	Other input variables	Patents	Publications	High-technology sector	Other output variables	
Tarnawska and Mavroeidis (2015)	R&D personnel	Expenditure on education per student	Intersectoral mobility of researchers	…	…	High-technology export (% exports)	SME with innovations (% of SMEs)	OO VRS; 25 EU countries; 2009 (inputs); 2012 outputs
Kou et al. (2016)	R&D personnel	R&D capital stock	Technology import; patents. Etc.	…	S&T_papers	Export of high-tech products	GDPP of employment	Multi-period, multi-division DEA model; 30 OECD countries; 2008–2010
Regional innovation systems								
Roman (2010)	Researchers	R&D expenditures	High- and medium-skilled labour	Patents	…	…	…	VRS OO; 14 regions of Romania, Bulgaria; 2003 (inputs), 2005 (outputs)
Guan and Chen (2010)	Full-time equivalent scientists and engineers in all sectors	R&D expenditure	…	Inventive patents	Published academic papers	…	New products	Non-radial DEA; 30 Chinese provinces; 2000–2003
Chen and Guan (2012)	STI personnel	STI expenditure	FDI; technology import; labour, etc.	Inventions; utility model	…	…	GDP; new products; export	Two-stage network model; 30 Chinese provinces; 1995–2007

Table 3 (continued)

Publication year and authors(s)	Input variables (in authors' terminology)			Output variables (in authors' terminology)				DEA model used; number of countries/regions; years of analysis
	Human Capital	R&D and education expenditures	Other input variables	Patents	Publications	High-technology sector	Other output variables	
Foddi and Usai (2013)	Population with tertiary education	Intramural R&D expenditure	Spatially lagged patents	EPO patent applications		…	…	CRS OO; VRS OO; 217 regions of European countries; 2000–2001 and 2003–2004 (inputs), 2003–2004 and 2006–2007 (outputs)
Xu and Cheng (2013)	Sci-tech and R&D faculty number	Sci-tech and R&D expenditures	New product expenditure	Patents	Scientific papers	…	GDP; new product, etc.	Two-Stage model; 30 provinces of China; 2001–2011
Broekel et al. (2013)	R&D employment	…	…	Patent applications	…	…	…	Input–output model; 150 Germany regions; 1999–2008
Li et al. (2014)	Intramural expenditure on R&D.	R&D personnel	…	Patent applications accepted	Scientific papers	…	National or industry standards	VRS OO; 30 provinces of China; 2010
Kaihua and Mingting (2014)	Scientists and engineers	R&D funding for applied research	…	Domestic patents	….	…	High-tech industries; new products	Two stage DEA; 30 provinces of china; 2002–2005

Table 3 (continued)

Publication year and authors(s)	Input variables (in authors' terminology)			Output variables (in authors' terminology)				DEA model used; number of countries/regions; years of analysis
	Human Capital	R&D and education expenditures	Other input variables	Patents	Publications	High-technology sector	Other output variables	
Liu et al. (2014)	R&D employment	R&D capital stock	…	Numbers of granted patents	Published S&T papers	…	…	Knowledge production DEA model; 30 provinces of China; 2001–2007
Zuo and Guan (2017)	Full-time equivalent researchers	Expenditure on R&D	…	Number of granted patents	…	…	…	Parallel DEA game model; 30 provinces of China; 2007 (inputs), 2010 (outputs)

Abbreviations of DEA models are interpreted as follows: *VRS* variable return to scale, *CRS* constant returns to scale, *OO* output oriented and *IO* input oriented

Table 4 Average RIS efficiency scores in the studied Russian region in 1998–2012. (Color figure online)

№	Region	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	average 1998-2012
11	Moscow City	1.000	0.884	0.753	0.684	0.572	0.670	0.676	0.768	0.753	0.828	0.852	0.766	0.989	0.923	1.000	0.808
28	Lipetsk Region	0.168	0.413	0.465	0.168	0.668	0.914	0.840	1.000	0.508	0.404	0.634	0.619	0.901	0.450	0.286	0.563
22	Kostroma Region	0.500	0.424	0.299	0.127	0.322	0.408	0.458	0.442	0.444	0.784	0.854	0.549	0.545	0.491	0.353	0.467
74	Tomsk Region	0.387	0.358	0.305	0.259	0.350	0.441	0.366	0.389	0.459	0.428	0.485	0.440	0.410	0.519	0.523	0.408
12	Saint-Petersburg	0.377	0.286	0.331	0.470	0.421	0.404	0.432	0.431	0.466	0.407	0.409	0.375	0.335	0.377	0.347	0.391
30	Moscow Region	0.306	0.317	0.232	0.300	0.320	0.492	0.438	0.381	0.369	0.428	0.465	0.326	0.288	0.284	0.353	0.353
15	Ivanovo Region	0.164	0.097	0.121	0.146	0.153	0.130	0.092	0.070		1.000	0.535	0.454	0.458	0.689	0.748	0.347
10	Voronezh Region	0.286	0.350	0.373	0.240	0.230	0.324	0.278	0.233	0.281	0.380	0.330	0.228	0.230	0.287	0.290	0.289
23	Krasnodar Krai	0.128	0.129	0.086	0.677	1.000	0.518	0.253	0.236	0.201	0.169	0.188	0.140	0.166	0.153	0.137	0.279
35	Novosibirsk Region	0.185	0.197	0.222	0.250	0.344	0.347	0.317	0.293	0.327	0.361	0.359	0.251	0.256	0.214	0.197	0.275
77	Ulyanovsk Region	0.295	0.240	0.249	0.307	0.247	0.325	0.276	0.290	0.424	0.268	0.233	0.203	0.228	0.235	0.242	0.271
9	Vologda Region	0.198	0.141	0.254	0.203	0.259	0.464	0.672	0.466	0.337	0.249	0.189	0.134	0.128	0.196	0.150	0.269
38	Oryol Region	0.174	0.178	0.186	0.250	0.288	0.311	0.307	0.393	0.303	0.260	0.249	0.277	0.320	0.298	0.180	0.265
45	Republic of Bashkortostan	0.331	0.237	0.234	0.272	0.245	0.243	0.267	0.220	0.243	0.302	0.245	0.206	0.218	0.202	0.202	0.244
42	Pskov Region				0.200	0.199			0.248	0.244	0.256	0.260	0.233	0.233	0.333	0.147	0.235
54	Republic of Mari El	0.200	0.090	0.104	0.095	0.080	0.208	0.142	0.126	0.167	0.135	0.391	0.451	0.340	0.416	0.551	0.233
40	Perm Krai	0.122	0.131	0.188	0.200	0.297	0.389	0.238	0.240	0.222	0.235	0.244	0.252	0.236	0.204	0.280	0.232
58	Tatarstan Republic	0.187	0.184	0.180	0.211	0.220	0.272	0.212	0.248	0.276	0.267	0.214	0.185	0.199	0.206	0.314	0.225
80	Chelyabinsk Region	0.592	0.227	0.160	0.200	0.196	0.188	0.154	0.209	0.242	0.239	0.274	0.177	0.163	0.143	0.191	0.224
33	Nizhniy Novgorod Region	0.296	0.197	0.159	0.185	0.214	0.320	0.295	0.239	0.220	0.191	0.194	0.146	0.157	0.147	0.184	0.210
20	Kemerovo Region	0.196	0.197	0.255	0.200	0.185	0.195	0.196	0.216	0.207	0.216	0.311	0.203	0.201	0.167	0.174	0.208
65	Ryazan Region	0.209	0.163	0.192	0.195	0.167	0.190	0.198	0.336	0.313	0.240	0.195	0.152	0.202	0.190	0.122	0.204
57	Republic of North Ossetia-Alania	0.314	0.200	0.183	0.121	0.222	0.268	0.210	0.206	0.247	0.131	0.199	0.150	0.199	0.169	0.201	0.201
76	Tyumen Region	0.198	0.135	0.221		0.265	0.272	0.226	0.200	0.223	0.206	0.211	0.171	0.169	0.154	0.147	0.200
75	Tula Region	0.113	0.112	0.270	0.215	0.246	0.255	0.226	0.227	0.223	0.241	0.161	0.157	0.122	0.182	0.123	0.192
25	Kurgan Region	0.072	0.060	0.100	0.120	0.168	0.139	0.159	0.197	0.212	0.272	0.213	0.230	0.193	0.376	0.345	0.190
26	Kursk Region	0.117	0.141	0.230	0.214	0.153	0.180	0.127	0.185	0.149	0.195	0.230	0.318	0.234	0.194	0.177	0.190
66	Samara Region	0.189	0.145	0.166	0.201	0.180	0.191	0.195	0.196	0.183	0.199	0.246	0.192	0.141	0.175	0.189	0.186
69	Sverdlovsk Region	0.135	0.151	0.167	0.178	0.215	0.179	0.202	0.179	0.182	0.186	0.248	0.199	0.174	0.203	0.166	0.184
18	Kaluga Region	0.162	0.116	0.126	0.200	0.275	0.225	0.177	0.159	0.164	0.232	0.241	0.170	0.114	0.242	0.150	0.183
63	Chuvash Republic	0.441	0.088	0.076		0.177	0.168	0.174	0.157	0.266	0.198	0.179	0.166	0.128	0.177	0.142	0.181
60	Udmurt Republic	0.136	0.120	0.127	0.121	0.182	0.138	0.200	0.199	0.158	0.232	0.296	0.187	0.266	0.124	0.173	0.177
73	Tver Region	0.162	0.161	0.185	0.218	0.155	0.203	0.216	0.173	0.237	0.199	0.192	0.162	0.137	0.122	0.112	0.176
47	Republic of Dagestan	0.099	0.125	0.125	0.200	0.100	0.132	0.087	0.147	0.076	0.117	0.187	0.163	0.267	0.143	0.549	0.168
83	Yaroslavl Region	0.158	0.129	0.095	0.131	0.133	0.179	0.186	0.185	0.182	0.205	0.172	0.119	0.158	0.172	0.224	0.162
64	Rostov Region	0.108	0.094	0.104	0.118	0.110	0.154	0.150	0.185	0.194	0.149	0.169	0.185	0.181	0.173	0.173	0.150
37	Orenburg Region	0.174	0.139	0.149	0.118	0.185	0.165	0.179	0.165	0.169	0.110	0.095	0.154	0.149	0.114	0.158	0.148
36	Omsk Region	0.081	0.059	0.086	0.116	0.133	0.178	0.226	0.169	0.205	0.157	0.187	0.159	0.160	0.162	0.140	0.148
1	Altai Krai	0.126	0.133	0.129	0.187	0.168	0.158	0.137	0.141	0.111	0.152	0.144	0.144	0.150	0.148	0.159	0.146
24	Krasnoyarsk Krai	0.095	0.078	0.076	0.100	0.121	0.139	0.133	0.127	0.141	0.126	0.220	0.156	0.129	0.183	0.285	0.141
39	Penza Region	0.075	0.080	0.083	0.133	0.106	0.103	0.134	0.129	0.109	0.145	0.112	0.124	0.243	0.180	0.237	0.133

Table 4 (continued)

№	Region	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	average 1998-2012
67	Saratov Region	0.108	0.085	0.077	0.103	0.088	0.105	0.147	0.142	0.149	0.176	0.154	0.140	0.142	0.186	0.161	0.131
72	Tambov Region	0.148	0.142	0.089	0.125	0.129	0.126	0.111	0.112	0.125	0.144	0.140	0.132	0.143	0.149	0.141	0.130
5	Belgorod Region	0.123	0.136	0.077	0.105	0.078	0.087	0.135	0.091	0.153	0.341	0.116	0.112	0.130	0.120	0.106	0.127
8	Volgograd Region	0.071	0.068	0.071	0.104	0.082	0.102	0.125	0.137	0.152	0.185	0.182	0.172	0.132	0.124	0.136	0.123
27	Leningrad Region	0.113	0.103	0.184	0.214	0.157	0.169	0.110	0.154	0.103	0.130	0.076	0.056	0.079	0.061	0.083	0.119
7	Vladimir Region	0.069	0.069	0.091	0.134	0.139	0.141	0.110	0.119	0.101	0.134	0.143	0.116	0.103	0.137	0.169	0.118
71	Stavropol Krai	0.112	0.101	0.099		0.076	0.103	0.094	0.101	0.137	0.165	0.151	0.150	0.119	0.101	0.114	0.116
78	Khabarovsk Krai	0.180	0.130	0.230	0.132	0.120	0.121	0.114	0.083	0.108	0.100	0.082	0.060	0.070	0.087	0.100	0.114
6	Bryansk Region	0.087	0.132	0.087	0.087	0.069	0.054	0.062	0.080	0.078	0.157	0.085	0.095	0.146	0.182	0.232	0.109
21	Kirov Region	0.084	0.065	0.110	0.152	0.130	0.135	0.144	0.095	0.080	0.103	0.082	0.099	0.110	0.098	0.101	0.106
2	Amur Region	0.142	0.087	0.106		0.057	0.096	0.105	0.114	0.099	0.093	0.127	0.113	0.110	0.126	0.103	0.106
4	Astrakhan Region	0.162	0.105	0.091	0.058	0.054	0.078	0.046	0.093	0.092	0.108	0.133	0.185	0.157	0.108	0.098	0.105
16	Irkutsk Region	0.096	0.062	0.076	0.247	0.100	0.097	0.073	0.075	0.099	0.114	0.109	0.093	0.089	0.084	0.111	0.102
41	Primorsky Krai	0.172	0.099	0.079	0.100	0.094	0.095	0.086	0.083	0.092	0.108	0.116	0.091	0.085	0.092	0.114	0.100
34	Novgorod Region	0.077	0.109	0.064	0.078	0.095	0.072	0.098	0.129	0.078	0.084	0.048		0.065	0.107	0.209	0.094
17	Kaliningrad Region	0.044	0.049	0.055	0.096	0.105	0.095	0.111	0.063	0.104	0.052	0.066	0.103	0.050	0.129	0.150	0.085
49	Kabardino-Balkar Republic			0.102	0.077	0.051	0.054	0.082	0.036	0.104	0.063	0.065	0.064	0.143	0.129	0.066	0.080
14	Zabaykalsky Krai				0.090	0.086	0.052	0.083	0.055			0.054	0.111	0.119	0.066	0.055	0.077
56	Republic of Sakha (Yakutia)	0.056	0.057	0.083	0.065	0.079	0.073	0.082	0.067	0.066	0.050	0.052	0.082	0.081	0.098	0.116	0.074
55	Republic of Mordovia	0.047		0.045	0.057	0.076	0.060	0.074	0.062	0.055	0.107	0.090	0.103	0.085	0.082	0.056	0.071
70	Smolensk Region	0.099	0.063	0.057		0.077	0.069	0.054	0.045	0.065	0.054	0.074	0.067	0.095	0.050	0.077	0.068
53	Komi Republic	0.095	0.125	0.064	0.060	0.075	0.047	0.070	0.063	0.066	0.073	0.047	0.030	0.041	0.051	0.096	0.067
52	Republic of Karelia			0.068										0.044	0.114	0.042	0.067
3	Arkhangelsk Region	0.114	0.066	0.076	0.078	0.055	0.064	0.031	0.049	0.086	0.077	0.047	0.028	0.053	0.092	0.041	0.064
46	Republic of Buryatia			0.061	0.060	0.038	0.068	0.074	0.038	0.055	0.051	0.061	0.071	0.054	0.068	0.098	0.061
31	Murmansk Region	0.023	0.026	0.056	0.030	0.037	0.030	0.055	0.052	0.076	0.058	0.070	0.040	0.035	0.050	0.060	0.047
85	**Average in a year**	**0.185**	**0.157**	**0.158**	**0.175**	**0.188**	**0.206**	**0.196**	**0.196**	**0.199**	**0.219**	**0.219**	**0.190**	**0.194**	**0.197**	**0.204**	**0.190**

The logic of colouring of regions is the following:

cells for a specific region in 1998–2012—green—the highest efficiency, red—the lowest efficiency for the whole matrix (i.e. colouring by year-region cells)

cells in “Average year”—green—the highest efficiency, red—the lowest efficiency for this row only

Table 5 Data source and time horizon for explanatory variables used in RIS efficiency model

RIS efficiency factor	Variables	Data source	Time horison
Embeddedness	Ln (the oldest university age)	University websites	1998–2012
	Ln (the Russian national Patents' stock)	Rospatent	1998–2012
Technological development	Ln (R&D expenditures per GRP)	Rosstat	1998–2012
	Ln (R&D expenditures per GRP)^2	Rosstat	1998–2012
Knowledge spillovers	Ln (potential interregional knowledge spillovers)	Authors' calculations (based on Rosstat data)	1998–2012
	Ln (distance to agglomeration with more than 1 mln. of residents)	Author calculations	1998–2012
RIS inner interactions	Ln (number of small enterprises per economically active population)	Authors' calculations (based on Rosstat data)	1998–2012
	Ln (number of high-technology start-ups per number of urban citizens with higher education)	Authors' calculations (based on RUSLANA data)	1998–2012
Industrial specialization	Ln (share of the processing industry in GRP)	Rosstat	1998–2012

RUSLANA is a dataset with comprehensive information on companies in Russia, Ukraine and Kazakhstan. RUSLANA database is operating by Bureau van Dijk

Rosstat Russian Federation Federal State Statistics Service, *Rospatent* Russian Federal Service for Intellectual Property

References

Abbasi, F., Hajihoseini, H., & Haukka, S. (2011). Use of virtual index for measuring efficiency of innovation systems: A cross-country study. *International Journal of Technology Management & Sustainable Development, 9*(3), 195–212.

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6*(1), 21–37.

Aldieri, L., Kotsemir, M. N., & Vinci, C. P. (2018). Knowledge spillover effects: Empirical evidence from Russian regions. *Quality & Quantity, 52*(5), 2111–2132.

Algieri, B. (2011). The Dutch disease: Evidences from Russia. *Economic Change and Restructuring, 44*(3), 243–277.

Asheim, B. T., & Gertler, M. S. (2005). The geography of innovation: Regional innovation systems. In *The Oxford handbook of innovation*.

Audretsch, B. (1998). Agglomeration and the location of innovative activity. *Oxford Review of Economic Policy, 14*(2), 18–29.

Audretsch, D., & Keilbach, M. (2004). Entrepreneurship capital and economic performance. *Regional Studies, 38*(8), 949–959.

Baburin, V., & Zemtsov, S. (2013). Geografiya innovatsionnykh protsessov v Rossii (Geography of innovation processes in Russia). *Vestnik Moskovskogo universiteta. Seriya 'Geografiya' (MSU Bulletin 'Geography, Environment, Sustainability'), 5,* 25–32. **(In Russian)**.

Baburin, V., & Zemtsov, S. (2014). Efficiency assessment of Russian regional innovation systems). In *Modernisation and innovation development of economic systems*. (pp. 18–37).

Bonaccorsi, A., & Daraio, C. (2004). Econometric approaches to the analysis of productivity of R&D systems. In *Handbook of quantitative science and technology research* (pp. 51–74). Dordrecht: Springer.

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies, 39*(1), 61–74.

Brenner, T., & Broekel, T. (2011). Methodological issues in measuring innovation performance of spatial units. *Industry and Innovation, 18*(1), 7–37.

Broekel, T. (2012). Collaboration intensity and regional innovation efficiency in Germany—A conditional efficiency approach. *Industry and Innovation, 19*(2), 155–179.

Broekel, T., Rogge, N., & Brenner, T. (2013) The innovation efficiency of German regions—A shared-input DEA approach. *Working Papers on Innovation and Space*, paper No. 8.

Broekel, T., Balland, P. A., Burger, M., & van Oort, F. (2014). Modeling knowledge networks in economic geography: A discussion of four methods. *The Annals of Regional Science*, *53*(2), 423–452.

Cazals, C., Florens, J.-P., & Simar, L. (2002). Nonparametric frontier estimation: A robust approach. *Journal of Econometrics, 106,* 1–25.

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.

Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (DEA)—Thirty years on. *European Journal of Operational Research, 192*(1), 1–17.

Cooke, P., Uranga, M. G., & Etxebarria, G. (1997). Regional innovation systems: Institutional and organisational dimensions. *Research Policy, 26*(4–5), 475–491.

Cooper, W. W., Seiford, L. M., & Tone, K. (2006). *Introduction to data envelopment analysis and its uses: With DEA-solver software and references*. Dordrecht: Springer.

Crescenzi, R., & Jaax, A. (2017). Innovation in Russia: The territorial dimension. *Economic Geography, 93*(1), 66–88.

Cullmann, A., Schmidt-Ehmcke, J., & Zloczysti, P. (2009). Innovation, R&D efficiency and the impact of the regulatory environment: A two-stage semi-parametric DEA approach. *Discussion paper No 883, German Institute for Economic Research, Berlin, May 2009*.

Dang, J., & Motohashi, K. (2015). Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. *China Economic Review, 35,* 137–155.

Debreu, G. (1951). The coefficient of resource utilization. *Economerica, 19*(3), 273–292.

Desai, R. M., Freinkman, L., & Goldberg, I. (2005). Fiscal federalism in rentier regions: Evidence from Russia. *Journal of Comparative Economics, 33*(4), 814–834.

Didenko, A., Abdikeev, N., & Loseva, O. (2011). Measuring efficiency of regional innovation system with DEA and PCA. In *Proceedings of IEEE 11th International Conference on Application of Information and Communication Technologies* (pp. 260–263).

Didenko, A., & Egorova, T. (2014). Innovations as factor of absorptive capacity of FDI spillovers across regions of Russian Federation. *Review of Business and Economics Studies, 2*(3), 75–85.

Dmitriev, M., Romashina, A., & Chistyakov, P. (2018). The role of spatial policy in acceleration of economic growth. *Social Sciences and Contemporary World, 5,* 31–47. **(In Russian)**.

Dupuit, J. (1848). *Etudes theoriques et pratiques sur le mouvement des eaux courantes*. Carilian-Goeury.

Eckstein, O. (1958). *Water resource development - the economics of project evaluation*. Cambridge, MA: Harvard University Press.

Emrouznejad, A., & Yang, G. L. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*, *61*, 4–8.

Fare, R., Grosskopf, S., & Lovell, C. A. K. (1994). *Production frontiers*. Cambridge: Cambridge University Press.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society Series A (General), 120*(3), 253–290.

Feldman, M. P. (1994). *The geography of innovation* (Vol. 2). Dordrecht: Springer.

Feldman, M. P. (2000). Location and innovation: The new economic geography of innovation, spillovers, and agglomeration. *The Oxford Handbook of Economic Geography, 1,* 373–395.

Florens, J. P., & Simar, L. (2002). Parametric approximations of nonparametric frontier. Discussion Paper No. 0222, Institut de Statistique, UCL, Belgium.

Foddi, M., & Usai, S. (2013). Technological catching up among European regions. Lessons from Data Envelopment Analysis. *SEARCH WORKING PAPER, paper No. WP4/02*.

Fritsch, M. (2003a). How and why does the efficiency of regional innovation systems differ? In *Innovation clusters and interregional competition* (pp. 79–96). Berlin, Heidelberg: Springer.

Fritsch, M. (2003b). Does R&D-cooperation behavior differ between regions? *Industry and Innovation, 10*(1), 25–39.

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. *Freiberg working papers*, paper No. 2006, 08.

Fritsch, M., & Slavtchev, V. (2007). Universities and innovation in space. *Industry and innovation, 14*(2), 201–218.

Fritsch, M., & Slavtchev, V. (2011). Determinants of the efficiency of regional innovation systems. *Regional Studies, 45*(7), 905–918.

Gambardella, A., Giuri, P., & Luzzi, A. (2007). The market for patents in Europe. *Research Policy, 36*(8), 1163–1183.

Gertler, M. S., Wolfe, D. A., & Garkut, D. (2000). No place like home? The embeddedness of innovation in a regional economy. *Review of International Political Economy, 7*(4), 688–718.

Griliches, Z. (Ed.). (2007). *R&D, patents and productivity*. Chicago: University of Chicago Press.

Guan, J., & Chen, K. (2010). Modeling macro-R&D production frontier performance: An application to Chinese province-level R&D. *Scientometrics, 82*(1), 165–173.

Guan, J., & Zuo, K. (2014). A cross-country comparison of innovation efficiency. *Scientometrics, 100*(2), 541–575.

Hall, P., & Simar, L. (2002). Estimating a changepoint, boundary or frontier in the presence of observation error. *Journal of the American Statistical Association, 97,* 523–534.

Han, U., Asmild, M., & Kunc, M. (2016). Regional R&D efficiency in Korea from static and dynamic perspectives. *Regional Studies, 50*(7), 1170–1184.

Hicks, J. R. (1939). The foundations of welfare economics. *The Economic Journal, 49*(196), 696–712.

Hudec, O., & Prochádzková, M. (2013). The relative efficiency of knowledge innovation processes in EU countries. *Studies in Regional Science, 43*(1), 145–162.

Hung, W. C., Lee, L. C., & Tsai, M. H. (2009). An international comparison of relative contributions to academic productivity. *Scientometrics, 81*(3), 703–718.

Kaihua, C., & Mingting, K. (2014). Staged efficiency and its determinants of regional innovation systems: A two-step analytical procedure. *The Annals of Regional Science, 52*(2), 627–657.

Kaldor, N. (1939). Welfare propositions of economics and interpersonal comparisons of utility. *The Economic Journal, 49*(145), 549–552.

Koopmans T. C. (1951). An analysis of production as efficient combination of activities. In T. C. Koopmans (Eds.), *Activity analysis of production and allocation*. Cowles Commission for Research in Economics, Monograph no. 13, New York.

Kotsemir, M. N. (2013). Measuring national innovation systems efficiency—A review of DEA approach. *Higher School of Economics Research Papers, paper No. WP BRP 16/STI/2013.*

Kou, M., Chen, K., Wang, S., & Shao, Y. (2016). Measuring efficiencies of multi-period and multi-division systems associated with DEA: An application to OECD countries' national innovation systems. *Expert Systems with Applications, 46,* 494–510.

Kuosmanen, T. (2008). Representation theorem for convex nonparametric least squares. *Econometrics Journal, 11,* 308–325.

Lee, H. Y., & Park, Y. T. (2005). An international comparison of R&D efficiency: DEA approach. *Asian Journal of Technology Innovation, 13*(2), 207–222.

Li, R., Li, Y., & Cui, Z. (2014). Application of data envelopment analysis to efficiency evaluation on R&D input and output. *Open Automation and Control Systems Journal, 6,* 194–199.

Liu, M. C., Wang, J. C., & Wu, M. T. (2014). Typology and knowledge productivity of regional innovation system: Evidence from China. *Journal of Business and Economics, 5*(1), 49–60.

Lu, W. M., Kweh, Q. L., & Huang, C. L. (2014). Intellectual capital and national innovation systems performance. *Knowledge-Based Systems, 71,* 201–210.

Marshall, A. (1890). *Principles of economics* (8th ed., p. 1920). London: Macmillan.

Meng, W., Hu, Z., & Liu, W. (2006). Efficiency evaluation of basic research in China. *Scientometrics, 69*(1), 85–101.

Murillo-Zamorano, L. R. (2004). Economic efficiency and frontier techniques. *Journal of Economic surveys, 18*(1), 33–77.

Nasierowski, W., & Arcelus, F. J. (2003). On the efficiency of national innovation systems. *Socio-Economic Planning Sciences, 37*(3), 215–234.

Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Cambridge: Belknap Press/Harvard University Press.

OECD Science, Technology and Innovation Outlook 2018: Adapting to Technological and Societal Disruption (2018).

Pan, T. W., Hung, S. W., & Lu, W. M. (2010). DEA performance measurement of the national innovation system in Asia and Europe. *Asia-Pacific Journal of Operational Research, 27*(03), 369–392.

Pareto, V. (1896). Cours d'économie Politique, reprinted as a volume of Oeuvres Com-pletes. Droz, Geneva (1965).

Perret, J. K. (2014). *Knowledge as a driver of regional growth in the Russian Federation*. Berlin: Springer.

Polanyi, M. (1967). *The tacit dimension*. Garden City, NY: Anchor.

Porter, M. E. (1998). *Clusters and the new economics of competition* (Vol. 76, No. 6, pp. 77–90). Boston: Harvard Business Review.

Roman, M. (2010). Regional efficiency of knowledge economy in the new EU countries: The Romanian and Bulgarian case. *Munich Personal RePEc Archive*, *paper No. MRPA 23083.*

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy, 94*(5), 1002–1037.

Rousseau, S., & Rousseau, R. (1997). Data envelopment analysis as a tool for constructing scientometric indicators. *Scientometrics, 40*(1), 45–56.

Rousseau, S., & Rousseau, R. (1998). The scientific wealth of European nations: Taking effectiveness into account. *Scientometrics, 42*(1), 75–87.

Rudskaia, I., & Rodionov, D. (2018). Construction of efficiency indicators for innovative activity in Russia's regions. *Review of Integrative Business and Economics Research, 7*(1), 16–43.

Seiford, L. M. (1996). Data envelopment analysis: The evolution of the state of the art (1978–1995). *Journal of Productivity Analysis, 7*(2–3), 99–137.

Sharma, S., & Thomas, V. (2008). Inter-country R&D efficiency analysis: An application of data envelopment analysis. *Scientometrics, 76*(3), 483–501.

Simar, L. (2003). *How to improve the performance of DEA/FDH estimators in the presence of noise?* Discussion Paper, Institut de Statistique, UCL, Belgium.

Staníčková, M., & Skokan, K. (2011). Evaluation of the EU member states competitive potential by data envelopment analysis. In *Proceedings of the 2nd international conference on mathematical models for engineering science* (pp. 190–195). World Scientific and Engineering Academy and Society (WSEAS).

Tarnawska, K., & Mavroeidis, V. (2015). Efficiency of the knowledge triangle policy in the EU member states: DEA approach. *Triple Helix, 2*(1), 1–22.

Tödtling, F., & Trippl, M. (2005). One size fits all?: Towards a differentiated regional innovation policy approach. *Research Policy, 34*(8), 1203–1219.

Tone, K. (2001). A slack-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 130,* 498–509.

Valdez Lafarga, C., & 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.

Walsh, J. P., Lee, Y. N., & Jung, T. (2016). Win, lose or draw? The fate of patented inventions. *Research Policy, 45*(7), 1362–1373.

WIPO. (2017). World Intellectual Property Indicators. Patents. https://www.wipo.int/edocs/pubdocs/en/wipo_pub_941_2017-chapter2.pdf.

Xu, L., & Cheng, M. (2013). A study on Chinese regional scientific innovation efficiency with a perspective of synergy degree. *Technology and Investment, 4*(04), 229–235.

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.

Zemtsov, S., & Baburin, V. (2016). Does economic-geographical position affect innovation processes in Russian regions? *Geography, Environment, Sustainability, 9*(4), 14–32.

Zemtsov, S., & Barinova, V. (2016). The paradigm changing of regional innovation policy in Russia: From equalization to smart specialization. *Voprosy Economiki, 10,* 65–81. **(In Russian)**.

Zemtsov, S., Muradov, A., Wade, I., & Barinova, V. (2016). Determinants of regional innovation in Russia: Are people or capital more important? *Foresight and STI Governance, 10*(2), 29–42.

Zemtsov, S. P., & Baburin, V. L. (2017). How to assess an efficiency of regional innovation systems in Russia? *Innovatsii, 2*(220), 60–66. **(In Russian)**.

Zemtsov, S. P., & Tsareva, Yu V. (2018). Entrepreneurial activity in the Russian regions: How spatial and temporal effects determine the development of small business. *Journal of the New Economic Association, 1*(37), 118–134.

Zhang, Y., & Bartels, R. (1998). The effect of sample size on mean efficiency in DEA with application to electricity distribution in Australia, Sweden and New Zealand. *The Journal of Productivity Analysis, 9,* 187–204.

Zubarevich, N. (2009). Regional development and regional policy in Russia during ten years of economic growth. *New Economic Association Journal, 1*(2), 61–174.

Zuo, K., & Guan, J. (2017). Measuring the R&D efficiency of regions by a parallel DEA game model. *Scientometrics, 112*(1), 175–194.