Alnafrah *Journal of Innovation and Entrepreneurship* (2021) 10:26
https://doi.org/10.1186/s13731-021-00159-3

Journal of Innovation and Entrepreneurship

RESEARCH

Open Access

Efficiency evaluation of BRICS's national innovation systems based on bias-corrected network data envelopment analysis

Ibrahim Alnafrah

Correspondence: ibrahimnafrah@gmail.com
Faculty of Economics, Damascus University, Damascus, Syria

Abstract

The very limited studies that tried to measure the efficiency of national innovation systems (NISs) in BRICS economies were limited to the assumption that the innovation process at national level consists of one stage only and got different and conflicting results. Therefore, this study endeavours to measure the efficiency of sub-processes within the BRICS's NISs and identify where the system failure lies in each NIS. Bias-corrected network data envelopment analysis (DEA) is used to measure the efficiency of total NIS and the efficiency of the other sub-processes within the system: (1) knowledge production process (KPP), and (2) knowledge commercialization process (KCP). The results showed that NISs in BRICS economies suffer from low performance in commercializing their outputs of universities and research organizations. While, on the other hand, their performance in creating scientific and technical knowledge is good in comparison to other studied countries. We suggest that the reason behind this imbalance is the network system failure associated with weak institutions and high uncertainty in the economy. In this study, we argue that the problem in BRICS NISs is not a problem of resources, but it is a problem of system management and institutions. Some bridging policies are suggested to be adopted by BRICS economies to improve their innovation performance and overcome the system failure of weak links between universities and industry.

Keywords: National innovation system, BRICS economies, Data Envelopment Analysis, DEA network, Knowledge commercialization, System failures

Introduction

Building a globally competitive economy today requires an economy with a high intensity of innovation activities at the national level. This innovativeness is a decisive factor that determines the potential of economic expansion and development of any economy since the economies of scale and low labour wages are no longer as decisive as they were two decades ago. Especially in emerging economies like BRICS economies. Therefore, there is a need for building an efficient national innovation system (NIS) in these countries in order to improve their economic competitiveness and sustainable economic growth based on innovation-related sources.

As a result of a highly competitive global environment, policymakers need to ensure that their innovation policies and strategies are sound and oriented precisely towards overcoming the weakness and shortcomings of their NIS. This process requires a profound analysis of NIS and all its actors, their relationships and the structural patterns of its progress overtime (Castellacci & Natera, 2013).

The notion of national innovation system as a systematic framework for studying creation, dissemination and exchanging of knowledge and technologies at the national level was firstly introduced by (Freeman, 1982; Freeman & Lundvall, 1988). This concept has been developed since that time to include all institutions, organizations and actors engaged in the innovation-related activities at sectoral, regional and national levels (Edquist, 2009; Nelson, 1993). The procedural objective of this conceptual framework is to study the relationships between the main actors within NIS and the needed mechanisms to develop these relationships to be more productive and efficient.

Existing literature that has studied NISs in developing economies such as BRICS economies was limited to four types of studies: (1) historical and theoretical analysis of NISs in BRICS countries (Cassiolato & Vitorino, 2009; Scerri et al., 2010; Zaichenko, 2014), (2) studying the causal relationship between NIS's variables and their impact on the economic development (Alnafrah & Bogdanova, 2018; Alnafrah et al., 2018; Rao-Nicholson et al., 2017), (3) using machine learning techniques to identify the structural strengths and weaknesses of NISs (Alnafrah, 2019; Alnafrah & Zeno, 2019), and (4) measuring the efficiency of specific innovation industries or sub-systems such as energy (Song et al., 2013; Tu et al., 2016), the insurance industry (Huang & Eling, 2013) and ICT sector (Biryukova & Matiukhina, 2019).

However, previous studies did not answer the following question: do the NISs in these economies work efficiently? The very limited studies that tried to measure the efficiency of NISs in BRICS economies based on conducting the Data Envelopment Analysis (DEA) were limited to the assumption that the innovation process at national level consists of one stage only (Cai & Hanley, 2012; Liu & White, 2001; Viotti, 2002). These studies treated NIS as one unit, neglecting the fact that the efficiency score of the total system does not demonstrate the sub-systems' efficiencies scores (Cron & Sobol, 1983; Kao & Hwang, 2008, 2010; Li et al., 2016; Wang et al., 1997).

Therefore, this study tries to answer the following questions: (1) Do the NISs in BRICS countries work efficiently? (2) What types of inefficiencies do these systems suffer from?

Drawing on the work of Carayannis et al. (2015), Cook et al. (2010), Guan and Chen (2012) and Li et al. (2016), we assume in this study that the innovation process at the national level consists of two main processes: (1) knowledge production process (KPP) and (2) knowledge commercialization process (KCP), where these two processes cover all functions of the NIS's actors: universities, business sector and government.

Accordingly, this study aims at measuring the efficiency of BRICS's NISs of two innovation-related processes and identifying where the system failure lies in each NIS.

This study endeavours to fill this research gap by conducting the data envelopment analysis (DEA) to provide the policymakers with profound insights about the structural functioning of their NISs. Moreover, this study provides the answer to the following question: are the BRICS's NISs working efficiently or not, and if they are not, what kind of system failure they suffer from and in which process?

This study is structured as follows. First, we revise the literature of NIS's efficiency studies in developing economies, in addition to those that have been conducted in BRICS economies. Second, we illustrate the data and methodology used in this study. Third, we present and discuss the results. Finally, we draw our conclusion and provide some recommendations.

Literature review

The development of economic activities as a result of utilizing the outputs of digital and technological revolution has led to increasing the intensity of innovations at micro, meso and macroeconomic levels. This kind of progress included radical changes in the productivity and the mechanisms of innovation creation and diffusion, which in its turn led policymakers to devise theoretical and practical frameworks to measure the impact of innovation activities on the national economic performance. In other words, there was a need to find a new analysis framework to help policymakers explain the way in which new innovations and technologies emerge and diffuse at the national level and how these technologies and innovations influence the overall socio-economic performance.

These conditions have led to the emergence of the NIS as a systemic framework for analysing the economic performance associated with innovative activities, creating, disseminating and exchanging high technologies (Freeman, 1982; Freeman & Lundvall, 1988; Godin, 2009; Lundvall, 2007). This analysis framework is used to study the relationships among the main actors within NIS and the needed mechanisms to develop these relationships and make them more productive and efficient. Accordingly, the concept of the NIS is an important conceptual framework in the context of studying and analysing the emergence and diffusion of new technologies and innovations at the national level (Metcalfe & Ramlogan, 2008).

That being said, the NIS concept has been witnessed three main shifts: (1) shift towards macro structures of NIS and the interactions between the main actors within the system (Chen & Guan, 2011); (2) shift towards technology, sectoral and regional innovation systems with special focus on the developing economies (Andersen et al., 2014; Malerba, 2002); and (3) growing emphasis on the internationalisation of NISs and the role of multinational corporations (MNCs) as a channel for global knowledge and innovation practices flows (Chung, 2002; Distefano et al., 2016; Watkins et al., 2015). These shifts paved the way for studying the NISs in developing economies, and especially those that have achieved and maintained high and extensive economic growth rates over a decade.

Regarding the NISs in BRICS economies, they were included gradually in the NIS literature because of two main reasons: (1) BRICS economies had not built yet mature NISs (Kravtsova & Radosevic, 2012), where their innovation activities were focused on specific sub-innovation processes in specific regions or industries (Watkins et al., 2015), (2) the economic openness and the development inclusion, that imposed the priority of building a national innovation network (Scerri & Lastres, 2013).

In this context and since the economic and social development of countries depends on a country's capacity to create, disseminate and apply new knowledge and technologies (Metcalfe & Ramlogan, 2008; Yao et al., 2009), it was important to ensure that NIS's functions and processes work efficiently. In doing so, several studies tried to measure the efficiency of NISs and other types of innovation systems (regional, sectoral and technology systems) in different countries, BRICS economies are included, to assess the role of these systems in the sustainability of economic growth (Afzal, 2014; Matei & Aldea, 2012; Samara et al., 2012; Tseng, 2009; Zemtsov & Kotsemir, 2019). Moreover, the efficiency measurement studies of innovation systems were oriented towards analysing the dynamic progress of these systems over time, in addition to identifying the system failures associated with low-efficiency levels (Guan & Chen, 2010, 2012).

Applying DEA approach is one of the most widespread methods of measuring the innovation system performance. Building on the work of (Emrouznejad & Yang, 2018), between 1980 and 2019, more than 4200 DEA-related articles were published in the Scopus database. This growing tendency indicates the importance and implication benefits that DEA provides in the field of efficiency measurement studies. In this paper, we are interested in the innovation system related studies since our aim is to measure and analyse the efficiency of the NISs in BRICS countries.

Innovation system is a multilevel concept (Carayannis et al., 2016), where national, regional and sectoral innovation system can coexist and coevolve together in the same country. Accordingly, the existing literature of measuring the efficiency of innovation systems is divided into three categories. First, studies that measure the efficiency of the NIS (NIS) (Abbasi et al., 2011; Guan & Chen, 2012; Sharma & Thomas, 2008; Wang & Huang, 2007). Second, studies that measure the efficiency of the regional innovation system (RIS) (Chen & Guan, 2012; Didenko et al., 2017; Guan & Chen, 2010; Lengyel & Leydesdorff, 2011; Zabala-Iturriagagoitia et al., 2007). Third, studies that measure the efficiency of the sectoral innovation system (SIS) (Andersen et al., 2014; Liu et al., 2018; Meng et al., 2006).

Regarding the efficiency analysis of NIS, there are several DEA-related articles in the existing literature. However, the most widespread studies are focused on developed economies such as EU and OECD (Hudec & Procházková, 2013; Kou et al., 2016; Matei & Aldea, 2012; Rousseau & Rousseau, 1997; Tarnawska & Mavroeidis, 2015).

However, most of previous studies that tried to evaluate the efficiency of NIS treated it as a one decision unit, which does not provide any insights to the policymakers (Grupp & Schubert, 2010; Jiménez-Sáez et al., 2011; Lee & Park, 2005; Namazi & Mohammadi, 2018; Pan et al., 2010; Ramanathan et al., 2018; Wang, Fan, et al., 2016; Zabala-Iturriagagoitia et al., 2007), leaving them with just an idea that their NIS works or does not work efficiently. Even this piece of information is not accurate enough to build on it any policy. In other words, the implication value of this kind of analysis is very low. What we are essentially arguing in this article is that measuring the efficiency of NIS should consider not only the overall innovation process but also all other sub-processes involved in this system.

Given the limitations of the previous DEA approaches, some studies applied additional econometric analyses such as Tobit regression (Afzal, 2014; Matei & Aldea, 2012) to investigate the impact of the environmental factors on the innovation performance, and super efficiency (Chen & Guan, 2012; Pan et al., 2010) to generate a corrected ranking system. However, these additional econometric analyses do not help in demonstrating the relationship and interactions of the innovation processes within the NIS. Therefore, network DEA approach was applied to analyse the interaction between sub-innovation processes within the NIS (Carayannis et al., 2015) and the path of productivity gain of national innovation systems and its relationship with the technological improvements in the context of catch up process (Zabala-Iturriagagoitia et al., 2020).

Accordingly and in line with the existing literature (Carayannis et al., 2016; Chen et al., 2018; Chen & Guan, 2012; Kou et al., 2016; Liou, 2009), we propose using DEA network by splitting the overall national innovation process into two sub-processes: knowledge production process (KPP) and knowledge commercialization process (KCP). By doing so, policymakers will be able to get some insights about the overall performance of their NIS in addition to the performance of other sub-processes, which in its turn will help them in identifying what kind of system failure they are dealing with and how the allocation of sources could be made better.

Interestingly, when it comes to the efficiency measurement of BRICS's NISs, the literature is very limited and cases study oriented. There are only three studies that have measured the efficiency of NISs in these countries together. Cai (2011) has studied the NISs of 22 countries including BRICS and G7. The findings of this study showed that BRICS's NISs have low performance in terms of their governance, in addition to a high dependency on natural resources. Cai argued that extensive economic growth does not enhance the competitiveness of BRICS economies. Therefore, he suggested transferring BRICS's factor-driven growth patterns into innovation-driven growth patterns. It is worth mentioning here that the absence of bias test for the efficiency results in this study led the author to inconsistent conclusions, for example, the negative relationship between the proxy variables of education system and the efficiency level of NIS. Cai and Hanley (2012) have studied BRICS's NISs by conducting two-stages DEA method. They found that technological similarity is not the only criterion underpinning innovative performance. They argued that the socio-economic conditions also play a role in determining the innovativeness of country. The findings of this study showed that China, India and Russia demonstrate relatively high-efficiency scores, whereas both Brazil and South Africa perform badly. Authors linked the "bad" performance of Brazil and South Africa with their strongly performing natural resources sector. In this context, it should be said that if that is so, how do the findings of this study explain the high-efficiency score of Russia? The main drawback of this study is treating the NISs as one decision unit omitting the fact that the national innovation performance cannot be analysed as one simple process with inputs and outputs. Brando Santana et al. (2015) supposed that technological innovation should positively contribute to achieving sustainable development. The results of this study showed that Brazil, South Africa and India have the highest efficiency scores among BRICS economies, whereas Russia and China have the worst innovation performance. Interestingly, the results of Brando Santana et al. (2015) study are exactly the opposite of the Cai and Hanley study (Cai & Hanley, 2012). We suggest that the reasons behind that are as follows: (1) choosing different variables to represent the inputs and outputs of NISs, for example the inputs in the Cai and Hanley study are outputs in the Brando et al. study, (2) using different scales and returns orientations and (3) using different bias test analysis.

Summing up, there were numerous studies that used the DEA methods to measure the efficiency of NISs. However, very limited studies conducted this analysis on BRICS's NISs, and those who used it got different and conflicting results because of various reasons as mentioned earlier. Therefore, this study endeavours to fill this research gap by (1) conducting bias-corrected DEA network analysis on the BRICS's NISs, and (2) considering the complexity of the national innovation activities by splitting the national innovation processes into two sub-processes.

Methodology and data

Drawing on the seminal work of Charnes et al. (1978) who proposed a nonparametric programming model (CCR)[1] to measure the efficiency of different decision making units (DMU), and the dual convex model (BCC)[2] introduced by Banker et al. (1984) to measure the technical and scale efficiency with reference to the efficient frontier, we use DEA method in this study to measure the relative efficiency scores of BRICS's NISs. However, these original DEA works were developed to measure the efficiency of DMU as a whole unit (Kao, 2014), without considering the performance of other sub-processes within this unit. Therefore, in this study, we use the advanced model of the DEA method, that is network DEA, which was introduced by Färe and Grosskopf (2000) and Wang et al. (1997).

The reason behind using such a method is that DEA does not assume any relative importance, weights or even mathematical hypotheses of inputs and outputs; besides, it is a nonparametric method that is less restrictive than parametric models. Moreover, the DEA is essentially based on the Pareto optimality principle (Charnes et al., 1985), where any decision-making unit is considered inefficient if any other decision-making unit or a combination of units were able to produce the same outputs by using fewer inputs than this unit used.

In this study, as mentioned earlier, the NIS was divided into two sub-processes:

- Knowledge production process (KPP): at this stage, the efficiency of the technical and scientific knowledge production process is measured. The main actors in this process are the universities and R&D organizations.
- Knowledge commercialization process (KCP): at this stage, the efficiency of the knowledge monetization process is measured. In other words, the efficiency of transforming technical and scientific knowledge into innovation products and new technologies. The inputs of this process are at the same time the outputs of the previous process (KPP), in addition to the other inputs that are not outputs of the KPP and related to the national innovation process.

The inputs and outputs of these two processes were taken at different time intervals with a time lag of 2 years between the inputs of the KPP and the outputs of the KCP.

As shown in Fig. 1, each process includes three inputs and two outputs variables (see the descriptive statistics of all included variables in Table 1).

In the Table 9 in Appendix, data used in this study is provided.

Selecting the sample of countries was based on two criteria. First, according to Cooper et al. (2006), the number of studied countries should be greater than the combined number of inputs and outputs. Otherwise, a large portion of studied countries will be identified as efficient due to an inadequate number of degrees of freedom. Accordingly, the number of studied countries should exceed the combined number of

[1]CCR abbreviation comes from model described in Charnes et al. (1978).
[2]BCC abbreviation comes from model described in Banker et al. (1984).

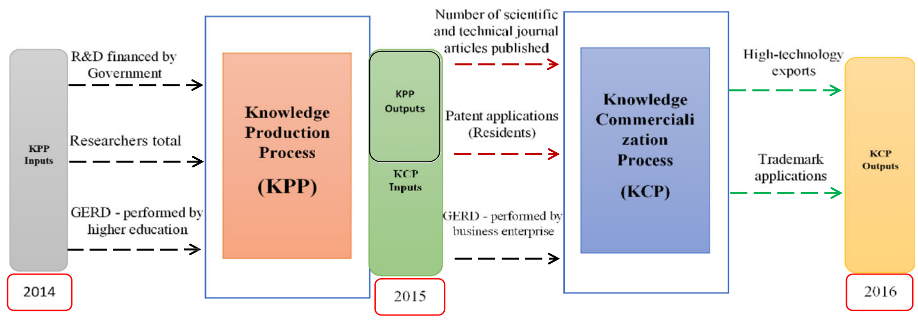

Fig. 1 NIS's sub-processes

inputs and outputs by several times. Second, we chose countries from the OECD group, where this group of countries is considered, to some extent, similar to the BRICS countries in terms of economic performance. We argue that comparing BRICS economies with other least developed economies will not help in showing the real innovation performance of this group of countries.

The methodology consists of three stages:

A. Inputs and outputs selection: this selection was based on an extended review of previous empirical studies that used different DEA methods to measure the efficiency of NIS-related processes as shown Table 10 in Appendix.

After that, a correlation matrix analysis was done to ensure that inputs and outputs have a significant correlation. The correlation matrixes of three NIS's processes are represented in Tables 2, 3 and 4.

The reason behind conducting the correlation matrixes analysis is to test the construct validity of our model (Golany & Roll, 1989; Lu et al., 2014). The results of the correlation matrixes analysis show that all inputs and outputs of all processes are significantly correlated. This means that the DEA model of NIS's sub-processes has high construct validity.

B. Returns selection: in order to select what kind of returns to scale we will use in our model, we draw on the work of Kneip et al. (2011) in identifying the return to scale (RTS) by conducting a RTS-test for all three processes: KPP, KCP and Total. The null hypothesis of this test is that the appropriate returns to scale are the constant returns to scale. The results of this test are represented in Table 5.

Results in Table 5 show that variable returns to scale (VRS) is the appropriate method to use for all processes, where the p value of all processes leads to rejecting the null hypothesis at α = 10%. This means that the variable returns to scale will be used in this study. In this context, it is worth mentioning that the RTS-test results are consistent with the structure of the studied NISs (DMUs) in this study, where all of them work at different scales. Moreover, the constant returns to scale method essentially measures scale efficiency without providing any information about the stage or the returns direction of the innovation activities. On the other hand, the variable returns to scale method measures the management efficiency of the innovation process regardless of the size of DMU. It is also better in identifying the future

Table 1 Descriptive statistics

Variable full name [abbreviated name] (unit of measurement)	Description	Data source	Type	Mean (all studied countries)	Std. deviation
R&D financed by Government [GERD Fin Gov] (in 2000 current PPP$)	R&D financed by Government refers to the financial resources that government allocates to support research and development activities.	UNESCO Institute for statistics	Input (KPP)	8,544, 208.14	15,600, 025.48
Researchers total [Res Tot] (units)	The number of researchers engaged in Research &Development (R&D). Researchers are professionals who conduct research and improve or develop concepts, theories, models techniques instrumentation, software of operational methods. R&D covers basic research, applied research and experimental development.	UNESCO Institute for statistics and World Bank	Input (KPP)	8,405,643	13,166, 765
GERD—performed by higher education [GERD Perf Educ] (in 2000 current PPP$)	GERD—performed by higher education refers to the financial resources that organizations of the education system allocate to conduct research and development activities.	UNESCO Institute for statistics and World Bank	Input (KPP)	241,187.52	380, 647.31
Number of scientific and technical journal articles published [S&T article] (units)	Scientific and technical journal articles refer to the number of scientific and engineering articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research.	World Bank	Output (KPP) /Input (KCP)	72,816.55	109, 070.63
Patent applications (Residents) [Pat appl] (units)	Patent applications are worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office for exclusive rights for an invention.	WIPO	Output (KPP)/Input (KCP)	63,533.04	199, 123.66
GERD—performed by business enterprise [Gerd Perf Bus] (in 2000 current PPP$)	GERD—performed by business enterprise refers to the financial resources that business sector allocates to conduct research and development activities.	UNESCO Institute for statistics	Input (KCP) /Intermediate	41,777, 881.65	90,936, 904.5
High-technology exports [HiTech Exp] (in current US$)	High-technology exports are products with high R&D intensity, such as in aerospace, computers, pharmaceuticals, scientific instruments and electrical machinery.	World Bank	Output (KCP)/Output (Total)	657,979, 280,133.28	754,871, 364,036.5
Trademark applications [TM Appl] (units)	Trademark applications filed are applications to register a trademark with a national or regional Intellectual Property (IP) office.	WIPO	Output (KCP) /Output (Total)	155,828.56	416, 881.69

directions of the national innovation policies, both at the level of knowledge production and the commercialization of this knowledge. It also should be noted that all studied NISs in this study operate under incomplete competition with different institutional structures. Therefore, the variable returns to scale will be adopted in this study.

Table 2 Correlations matrix (KPP)

	GERD Fin Gov	Res Tot	GERD Perf Educ	S&T articl	Pat Appl
GERD Fin Gov	1	.800**	.966**	.965**	.829**
Res Tot	.800**	1	.828**	.882**	.522**
GERD Perf Educ	.966**	.828**	1	.978**	.872**
S&T articl	.965**	.882**	.978**	1	.824**
Pat Appl	.829**	.522**	.872**	.824**	1

** represents significance at 5% level of significance

C. Orientation selection: Input-oriented model with variable returns to scale was selected in the knowledge production process (KPP), where actors in general, and the government in particular, are able to control inputs more than outputs at this stage. In addition, this stage is the first stage in the innovation process, thus focusing on the input side to build the national innovation and technological capabilities and capacities needed to produce scientific and technical knowledge is the core objective at this stage. Regarding the knowledge commercialization process (KCP), output-oriented model with variable returns to scale was selected since the main objective of the companies and the system is to maximize the outputs of the innovation process as much as possible.

Efficiency measurement model

We have two processes, where each DMU, NIS in this study, has m^1 inputs $X_{i^1 j}$ ($i^1 = 1, \ldots, m^1$) and s^1 outputs $Y_{r^1 j}$ ($r^1 = 1, \ldots, s^1$) for the KPP, and has m^2 inputs $X_{i^2 j}$ ($i^2 = 1, \ldots, m^2$) and s^2 outputs $Y_{r^2 j}$ ($r^2 = 1, \ldots, s^2$) for the KCP. Moreover, there are P intermediate Z_{pj} ($p = 1, \ldots, q$). These intermediates are the link between the KPP and KCP. Let u_{r^1}, u_{r^2}, v_{i^1}, v_{i^2} and w_p denote unknown positive values above ε (non-Archimedean number).

The overall efficiency of NIS can be defined as follows:

$$E_j = \frac{\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} + \sum_{p=1}^{q} w_p z_{pj}}{\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj}} \tag{1}$$

$\boldsymbol{E_j}$ is the ratio of the aggregated weighted outputs to the aggregated weighted inputs of the two processes. The overall efficiency $\boldsymbol{E_j}$ is a combination of two efficiencies E_j^1 for the KPP efficiency score and E_j^2 for the KCP efficiency score. So, the overall convex efficiency can be defined as follows:

Table 3 Correlations matrix (KCP)

	S&T articl	Pat Appl	GERD Perf Bus	HiTech Exp	TM Appl
S&T articl	1	.824**	.980**	.928**	.773**
Pat Appl	.824**	1	.823**	.719**	.978**
GERD Perf Bus	.980**	.823**	1	.930**	.742**
HiTech Exp	.928**	.719**	.930**	1	.640**
TM Appl	.773**	.978**	.742**	.640**	1

** represents significance at 5% level of significance

Table 4 Correlations matrix (Total)

	GERD Fin Gov	Res Tot	GERD Perf Educ	HiTech Exp	TM Appl
GERD Fin Gov	1	.800**	.966**	.879**	.799**
Res Tot	.800**	1	.828**	.909**	.415*
GERD Perf Educ	.966**	.828**	1	.906**	.816**
HiTech Exp	.879**	.909**	.906**	1	.640**
TM Appl	.799**	.415*	.816**	.640**	1

**, * represent significance at 5 and 10% level of significance, respectively

$$E_j = \omega_j\, E_j^1 + (1 - \omega_j) E_j^2 \quad (2)$$

where

$$E_j^1 = \frac{\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj}}{\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j}} \in (0, 1] \quad (2.1)$$

and

$$E_j^2 = \frac{\sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j}}{\sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj}} \in (0, 1] \quad (2.2)$$

and

$$\omega_j = \frac{\sum_{i1=1}^{m1} v_{i_1} x_{i1\,j}}{\sum_{i1=1}^{m1} v_{i_1} x_{i1\,j} + \sum_{i2=1}^{m2} v_{i_2} x_{i2\,j} + \sum_{p=1}^{q} w_p z_{pj}} \in [0, 1] \quad (2.3)$$

ω_j denote the utilized portion of system aggregate inputs in the KPP, while 1-ω_j is the utilized portion of the system aggregate inputs in the KCP.

Based on Kao and Hwang (2008), the outputs of the first process (KPP) should be the inputs of the second process (KCP). So, the CRS model (Charnes et al., 1978) of the overall efficiency of a DMU_{j_0} can be calculated as follows:

Table 5 RTS-Test of returns to scale

Process	Orientation	*P* value	Decision
KPP	**Input**	0.001***	Reject H_0
	Output	0.05*	Reject H_0
KCP	**Input**	0.05*	Reject H_0
	Output	0.05*	Reject H_0
Total	**Input**	0.02**	Reject H_0
	Output	0.02**	Reject H_0

***, **, * represent significance at 1, 5 and 10% level of significance, respectively

$$\begin{aligned} E_{j_0} = {} & \max \frac{\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0}}{\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0}} \\ \text{s.t.} \quad & \frac{\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} + \sum_{p=1}^{q} w_p z_{pj}}{\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj}} \le 1 \\ & \frac{\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj}}{\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j}} \le 1 \\ & \frac{\sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j}}{\sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj}} \le 1 \end{aligned} \tag{3}$$

where u_{r^1}, u_{r^2}, v_{i^1}, v_{i^2} and $w_p \ge \varepsilon$; $j = 1, 2, \ldots, n$

Transformation of the previous model into a linear program model can be solved as follows:

$$\begin{aligned} E_{j_0} = {} & \max \sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \\ \text{s.t.} \quad & \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} = 1 \\ & \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj} \right) - \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} \le 0 \\ & \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} - \left(\sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj} \right) \le 0 \end{aligned} \tag{4}$$

where u_{r^1}, u_{r^2}, v_{i^1}, v_{i^2} and $w_p \ge \varepsilon$; $j = 1, 2, \ldots, n$

In the same way, we calculate the efficiency of two sup-processes (KPP and KCP).

$$\begin{gathered} E^1_{j_0} = \max \sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \\ \text{s.t.} \quad \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} = 1 \\ \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} \right) - E_{j_0} \left(\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \right) = 0 \\ \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj} \right) - \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} \le 0 \\ \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} - \left(\sum_{p=1}^{q} w_p z_{pj} + \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} \right) \le 0 \end{gathered} \tag{5}$$

where u_{r^1}, u_{r^2}, v_{i^1}, v_{i^2} and $w_p \ge \varepsilon$; $j = 1, 2, \ldots, n$
and

$$\begin{gathered} E^2_{j_0} = \max \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \\ \text{s.t.} \quad \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} = 1 \\ \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} \right) - E_{j_0} \left(\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \right) = 0 \\ \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj} \right) - \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} \le 0 \\ \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} - \left(\sum_{p=1}^{q} w_p z_{pj} + \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} \right) \le 0 \end{gathered} \tag{6}$$

where u_{r^1}, u_{r^2}, v_{i^1}, v_{i^2} and $w_p \ge \varepsilon$; $j = 1, 2, \ldots, n$

All previous models (Eqs. 1 to 6) work under the assumption of constant returns to scale (CRS) and outputs oriented, but the RTS-test showed that the appropriate model is the variable returns to scale (VRS) with an inputs-oriented model for the KPP and outputs-oriented for the KCP and the overall innovation process. Therefore, deriving from Banker et al. (1984), Chen et al. (2009), Didenko et al. (2017), Guan and Chen (2012) and Wang and Chin (2010), the previous models are transformed as follows:

VRS-output-oriented model of the overall innovation process (NIS)

The primal equation of VRS-output-oriented model is as follows:

$$\begin{aligned} \theta_{j_0} = \ & \min \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} - \mu_{j_0}^1 - \mu_{j_0}^2 \\ \text{s.t.} \ & \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj} - \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} \right) - \mu_{j_0}^1 - \mu_{j_0}^2 \geq 0 \\ & \sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} = 1 \end{aligned} \tag{7}$$

where u_{r^1}, u_{r^2}, v_{i^1}, v_{i^2} and $w_p \geq \varepsilon$; $j = 1, 2, \ldots, n$

$\mu_{j_0}^1$ and $\mu_{j_0}^2$ represent the direction of returns and they are free of sign scalers that used in the VRS model. So, if $\mu_{j_0} > 0$, this means we have decreased returns; if $\mu_{j_0} < 0$, this means we have increased returns; and if $\mu_{j_0} = 0$, then the returns are constant.

The dual linear programming model is as follows:

$$\begin{aligned} & \max \theta_0 \\ \text{s.t.} \ & \theta_0 \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \right) - \left(\sum_{r^1=1}^{s^1} \lambda_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} \lambda_p z_{pj} + \sum_{r^2=1}^{s^2} \lambda_{r_2} Y_{r^2 j} \right) \leq 0 \\ & \left(\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \right) - \left(\sum_{i^1=1}^{m^1} \lambda_{i_1} x_{i^1 j} + \sum_{i^2=1}^{m^2} \lambda_{i_2} x_{i^2 j} + \sum_{p=1}^{q} \lambda_p z_{pj} \right) \geq 0 \\ & \sum_{j=1}^{n} \lambda_j = 1 \end{aligned} \tag{8}$$

where $\lambda_j \geq 0$ and represents the associated weighting of outputs and inputs of $\mathrm{DMU_j}$.

VRS-input-oriented model of KPP

The primal equation of VRS-input-oriented model is as follows:

$$\begin{aligned} \theta_{j_0}^1 = \ & \max \sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} + \mu_{j_0}^1 \\ \text{s.t.} \ & \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} - \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj} \right) \geq 0 \\ & \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} = 1 \end{aligned} \tag{9}$$

where u_{r^1}, u_{r^2}, v_{i^1}, v_{i^2} and $w_p \geq \varepsilon$; $j = 1, 2, \ldots, n$

The dual linear programming model is as follows:

$$\begin{aligned} & \min \theta_{j_0}^1 \\ \text{s.t.} \ & \left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \right) - \left(\sum_{r^1=1}^{s^1} \lambda_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} \lambda_p z_{pj} \right) \leq 0 \\ & \theta_{j_0}^1 \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} - \sum_{i^1=1}^{m^1} \lambda_{i_1} x_{i^1 j} \geq 0 \\ & \sum_{j=1}^{n} \lambda_j = 1 \\ & \lambda_j \geq 0 \end{aligned} \tag{10}$$

VRS-output-oriented model of KCP

The primal equation of VRS-output-oriented model is as follows:

$$\begin{aligned} &\theta_{j_0}^2 = \min \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} - \mu_{j_0}^2 \\ \text{s.t.} \quad &\left(\sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj}\right) - \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} - \mu_{j_0}^2 \geq 0 \\ &\sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} = 1 \end{aligned} \tag{11}$$

where u_{r^1}, u_{r^2}, v_{i^1}, v_{i^2} and $w_p \geq \varepsilon$; $j = 1, 2, \ldots, n$

The dual linear programming model is as follows:

$$\begin{gathered} \max \theta_{j_0}^2 \\ \text{s.t.} \quad \theta_{j_0}^2 \sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} - \sum_{r^1=1}^{s^1} \lambda_{r_1} Y_{r^1 j} \leq 0 \\ \left(\sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0}\right) - \left(\sum_{i^2=1}^{m^2} \lambda_{i_2} x_{i^2 j} + \sum_{p=1}^{q} \lambda_p z_{pj}\right) \geq 0 \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \geq 0 \end{gathered} \tag{12}$$

All previously formulated equations are not bias corrected, where the efficiency scores of DEA are subject to sampling variation of frontier (Tsolas, 2011). The core idea behind the bootstrapping is to estimate the efficiency scores based on multiple sampling process (Simar & Wilson, 1998). To avoid the bias of the $\widehat{\theta}_i$ value to one, we generate a simulated data that is approximately equivalent to the original one (Kneip et al., 2011; Simar & Wilson, 2007). The distributions and standard deviations of the bootstrapped samples are close to the original data. Accordingly, the bias corrected efficiency score can be formulated as follows:

$$\tilde{\theta}_j = \hat{\theta}_j - Bias\left(\hat{\theta}_j\right) \tag{13}$$

Where

$$Bias\left(\hat{\theta}_j\right) = E\left(\hat{\theta}_j\right) - \hat{\theta}_j = B^{-1} \sum_{b=1}^{B} \hat{\theta}^*{}_{jb} - \hat{\theta}_j$$

$$\tilde{\theta}_j = 2\hat{\theta}_j - B^{-1} \sum_{b=1}^{B} \hat{\theta}_{jb}^* \left(\hat{\theta}_j\right) \tag{14}$$

where b = 1…, B is a sample generated from $\hat{\theta}_1$ to $\hat{\theta}_j$.

Results and discussion

As shown in Table 6, the results of VRS-input-oriented model show that only 10 of 24 countries are efficient in producing scientific and technical knowledge (KPP), whereas the results of VRS-output-oriented model show that only 12 of 24 countries are efficient in terms of commercializing this knowledge (KCP). On the other hand, the results of DEA for the total innovation process show that only 13 of 24 countries are efficient. However, none of all studied countries was efficient without being efficient at least in one sub-process. It should be mentioned here that the VRS model measures the efficiency of resources management, not the scale efficiency because all studied NISs work under different scales.

Regarding the efficiency scores of the BRICS NISs, all of them were ranked at the bottom of the studied countries list. Moreover, BRICS economies suffer from low performance in terms of knowledge commercialization, where all of them have a very low-efficiency score in comparison to other studied countries. On the other hand, the

Table 6 DEA network results

DMU	KPP efficiency score	Bias-corr.KPP efficiency score	KPP.Rank	KCP efficiency score	Bias-corr.KCP efficiency score	KCP.Rank	Total efficiency score	Bias-corr.Total efficiency score	Total.Rank	Average Efficiency Score	Final Efficiency Rank
RU	**0.60**	**0.51**	**23**	**0.52**	**0.32**	**15**	**0.60**	**0.46**	**19**	**0.43**	**23**
CN	**1**	**0.77**	**10**	**1**	**0.24**	**19**	**1**	**0.52**	**15**	**0.51**	**17**
IND	**1**	**0.81**	**4**	**1**	**0.39**	**10**	**1**	**0.44**	**20**	**0.55**	**14**
BRA	**1**	**0.76**	**11**	**1**	**0.29**	**17**	**1**	**0.37**	**22**	**0.47**	**21**
ZAF	**1**	**0.71**	**16**	**1**	**0.14**	**23**	**1**	**0.55**	**13**	**0.47**	**22**
AUT	0.64	0.53	22	0.36	0.20	21	0.35	0.25	24	0.32	24
BEL	0.81	0.67	20	1	0.45	5	0.89	0.65	5	0.59	4
CAN	0.93	0.79	7	0.70	0.41	9	0.74	0.55	14	0.58	6
DNK	1	0.75	14	0.40	0.26	18	1	0.48	17	0.50	19
FIN	0.99	0.85	2	0.30	0.17	22	0.95	0.69	2	0.57	10
FRA	0.57	0.50	24	0.95	0.62	2	0.78	0.61	10	0.57	8
DEU	0.69	0.58	21	1	0.36	11	1	0.64	6	0.53	15
ITA	1	0.79	9	0.66	0.44	6	0.62	0.47	18	0.57	11
KOR	1	0.79	8	0.70	0.43	7	0.69	0.49	16	0.57	9
NLD	0.79	0.67	19	1	0.42	8	1	0.63	7	0.57	7
NOR	0.99	0.85	1	1	0.32	16	1	0.60	11	0.59	3
POL	0.95	0.81	5	0.54	0.35	12	0.44	0.33	23	0.50	18
PRT	1	0.76	13	1	0.11	24	1	0.61	9	0.49	20
SGP	0.79	0.69	18	1	0.34	13	1	0.65	4	0.56	12
ESP	0.91	0.81	6	0.77	0.47	4	0.54	0.37	21	0.55	13
SWE	0.84	0.70	17	0.38	0.23	20	0.83	0.63	8	0.52	16
TUR	0.86	0.76	12	1	0.59	3	1	0.65	3	0.67	2
UK	1	0.73	15	0.95	0.67	1	1	0.74	1	0.71	1
USA	1	0.82	3	1	0.34	14	1	0.59	12	0.58	5

Final efficiency rank is the average ranking value of three processes: KPP, KCP and total innovation process

performance of BRICS economies in terms of knowledge production is better than their performance in commercializing this knowledge, where India and China perform well in comparison to other BRICS countries.

To identify what measures need to be taken to make the knowledge production and knowledge commercialization processes work efficiently, a projection analysis was done. The values of projection analysis, as shown in Table 7, were calculated through the Eqs. 8, 10 and 12. The results in Table 7 show how much countries should decrease their innovation inputs, in inputs-oriented model, or increase innovation outputs, in outputs-oriented model, to work at optimal scale with the best possible efficient performance.

Table 7 DEA's projection results

DMU	KPP Projections			KCP Projections		Total Projections	
	R&D financed by Government	Researchers total	GERD - performed by higher education	High-technology exports	Trademark applications	High-technology exports	Trademark applications
RU	**-60.1**	**-60.1**	**-33.5**	**193.3**	**193.3**	**166.2**	**166.2**
CN	**100**	**100**	**100**	**100**	**100**	**100**	**100**
IND	**100**	**100**	**100**	**100**	**100**	**100**	**100**
BRA	**100**	**100**	**100**	**100**	**100**	**100**	**100**
ZAF	**100**	**100**	**100**	**100**	**100**	**100**	**100**
AUT	-56	-50.6	-64.5	280.7	280.7	285	285.0
BEL	-80.6	-80.6	-80.6	100	100	112.6	112.6
CAN	-93.2	-67.2	-93.2	142.6	142.6	134.9	134.9
DNK	100	100	100	250.1	601.7	100	100
FIN	-99.5	-99.5	-86.4	332.7	385.7	105.1	547
FRA	-57.1	-57.1	-57.1	105.7	105.7	129.0	129
DEU	-55.8	-68.9	-68.9	100	100	100	100
ITA	100	100	100	151.3	151.3	160.9	160.9
KOR	100	100	100	142	142	145.9	145.9
NLD	-78.6	-71	-78.6	100	100	100	100
NOR	-98.2	-85.4	-98.2	100	100	100	100
POL	-95.1	-95.1	-95.1	183.8	525	226.9	226.9
PRT	100	100	100	100	100	100	100
SGP	-78.8	-55.6	-78.8	100	100	100	100
ESP	-91.3	-91.3	-91.3	129.8	129.8	186.1	186.1
SWE	-83.6	-63.5	-83.6	260.4	260.4	120.8	120.8
TUR	-85.9	-62.5	-85.9	100	100	100	100
UK	100	100	100	106.7	106.7	100	100
USA	100	100	100	100	100	100	100

The projection results are linked to the orientation models of each process, where the table includes the projection results of the inputs of the KPP since the KPP is input oriented. The results also show only the projection values of outputs variables for both KCP and total innovation process since these two processes are output oriented

A country like Russia, for example, suffers from a low performance at both innovation-related processes: KPP and KCP. The projections analysis in Appendix, of KPP efficiency score in Russia shows that if Russia wants to achieve the KPP efficiency score of 100% (1.00) with the current level of output variables, Russia should decrease expenditure on R&D by government and education sector (X1 and X3) by 60.1% and the number of researchers (X2) by 33.5%. These figures indicate incompetence in managing the inputs of KPP. In other words, this low performance at both innovation-related processes represents the waste of resources that can be reallocated in other areas such as creating business incubators, innovation parks and technological clusters.

In the same context, the projection analysis of KCP efficiency score in Russia shows that if Russia wants to achieve the KCP efficiency score of 100% (1.00), it should increase outputs of the knowledge commercialization process by 93.3%. This means that the Russian innovation system has very low performance in terms of transforming the outputs of KPP into innovation products and services. This situation reveals a network system failure associated with weak linkages among universities and industry because of many institutional obstacles that generate a high-risk business environment and market uncertainty (Hekkert et al., 2007; Klein Woolthuis et al., 2005). This means that the problem in the Russian innovation system is not a problem of resources, but it is a problem of system management and institutions. This situation can be found in all other BRICS economies in different forms.

For a more in-depth analysis of the efficiency analysis results, we analyse the correlation matrix between the three models (KPP, KCP and total). The correlation matrix among these three processes shows the causal relationship between the overall innovation process and the sub-processes: (1) the KPP, (2) and the KCP.

According to the DEA results, NISs can be classified into four groups as shown in Fig. 2.

A. Innovation latecomers: this group includes the weakest innovation systems, where both KPP and KCP do not work efficiently. As mentioned earlier, this is mainly due to poor resources management at scales that are disproportionate to the intensity and development level of innovative and technological activities. These countries need to reduce the KPP inputs and focus on reallocating their resources

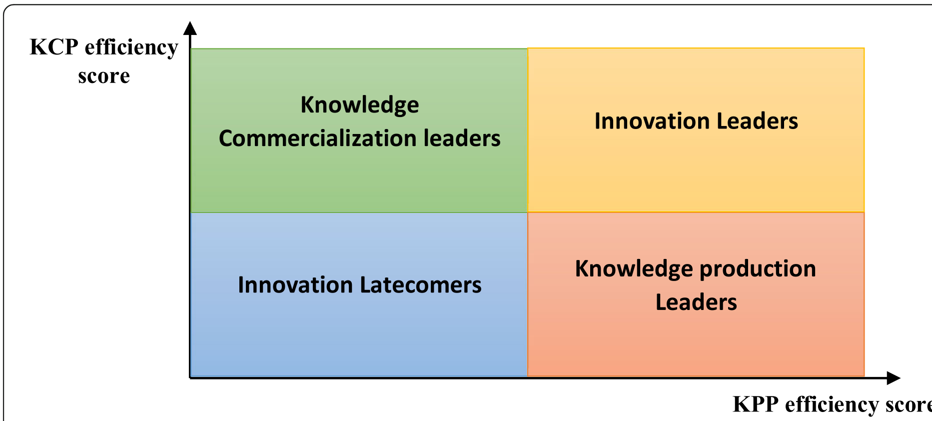

Fig. 2 NISs classification matrix

based on adopting new management paradigms. Without doing so, any further investments in the KCP will be futile as long as the outputs of KPP are low.

B. Knowledge production leaders: this group includes NISs with a good education system with a good efficiency score of KPP. However, the commercialization process of the outputs of KPP does not work efficiently. Therefore, these countries should improve the synergistic relationships between main NIS's actors by building bridging organizations, enablers and a stimulating institutional environment. Moreover, promoting trade openness and protecting intellectual property rights are essential prerequisites for utilizing patents and technology transfer.
C. Knowledge commercialization leaders: this group includes NISs that have a good performance in commercializing their knowledge. However, the KPP in universities in these NISs is not up to the level of development of innovation activities in the industry. This situation leads to a weak innovation performance at the national level. This group of countries needs to reallocate R&D resources into improving the KPP performance. In other words, enhancing mechanisms and dynamics of knowledge production in universities and research centers by supporting them through grants programs oriented towards specific national technological priorities. In addition to creating joint research programs gathering universities with business sector.
D. Innovation leaders: this group includes NISs that have a very good performance at both KPP and KCP. Countries in this group are efficient at resources management and thy work at a good scale. To maintain their leadership, these countries need to increase their innovation inputs and constantly invest in new technologies as a part of a leadership strategy. This kind of innovation behaviour has a direct impact on national wealth creation.

In consistent with the previous theoretical illustration, studied NISs were classified based on the bias-corrected efficiency scores results of the DEA analysis as shown in Fig. 3.

Since all studied countries have a high efficiency score in KPP, we have raised the threshold to 0.6. On the other hand, there are not many countries they have a high efficiency score in KCP; therefore, we lowered the threshold to 0.4. As shown in the previous figure, all NISs of BRICS economies, except Russia, belong to the knowledge production leaders' group. This indicates that these countries lack effective mechanisms to transform the outputs of KPP into innovation products and new technologies. The good performance of KPP in these countries is associated with low performance in commercializing the outputs of KPP. Therefore, BRICS economies need to focus their efforts on building enablers and bridging relationships between universities and industry by supporting intermediary firms and intermediary actors. These intermediary actors are considered a key element in increasing synergy among NIS's actors and facilitating the flow of knowledge, practices and technologies among them.

Regarding the foreign investment-related policies, BRICS countries need to promote free markets and free trade and build the legal and institutional environment that stimulates the influx of foreign companies involved in innovation, not just those looking for low wage labour.

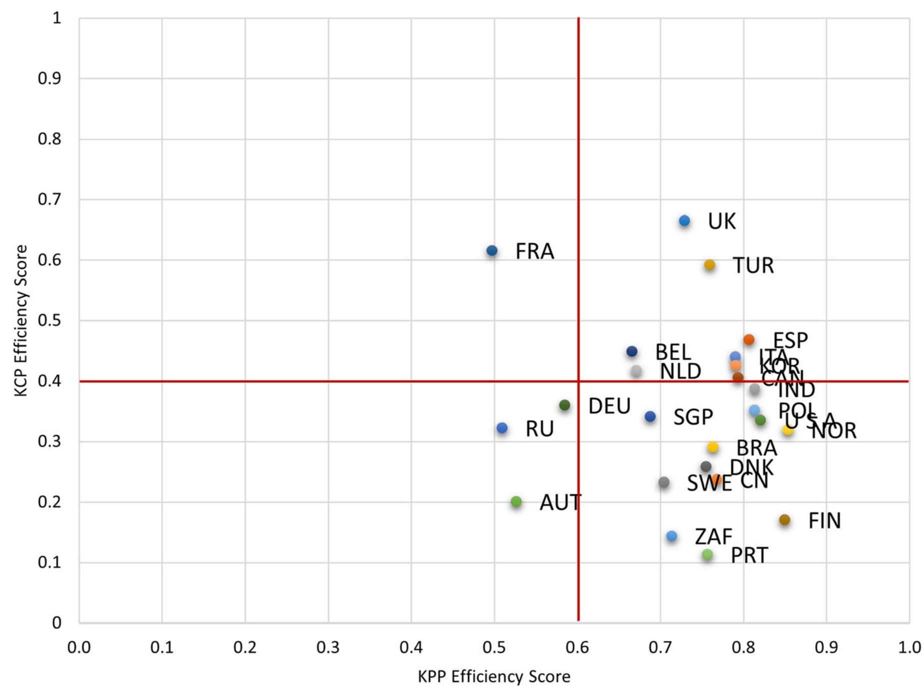

Fig. 3 NISs classification based on bias-corrected DEA results

In this context, it should be mentioned that the weak link between the KPP and KCP can by caused by many other economic, political and cultural factors. For instance, Krasikova and Ognev (2014) showed that corruption in the innovation activities of universities reduces the productive interactions of them with business sector and government. In the same context, Lobazova (2019) emphasized the role of mentality of corruption as a factor hampering innovation. On the other hand, other studies addressed the direct negative influence of political instability on the innovation system (Allard et al., 2012; Namazi & Mohammadi, 2018; Pertuze Salas et al., 2019).

Regarding the political economy of the way in which the innovation system works, it can be said that the lack of institutional capacities and the weak role of the low play a decisive role in shifting the innovation strategies of the main actors in the innovation system from a partnership strategies to a lobby or corruption strategies (Fagerberg et al., 2009; Gao & Yuan, 2020; Papaioannou et al., 2016). In consistence with the results of our study, we argue that most of BRICS countries suffer from the hindering effects of all previous environmental factors. These factors play an important role in shaping the political economy of innovation in this group of countries.

The aforementioned policies should coincide with a strong presence of government as a key coordinating actor in the innovation system whose main task is to stimulate entrepreneurial activities, effectively manage productive innovation relationships and create incentives for these types of activities.

The results of DEA show that some countries have a good total efficiency score, but they have low-efficiency scores in KPP or KCP. On the other hand, other countries such as BRICS countries have a low total efficiency score combined with high efficiency score of KPP and low efficiency score of KCP. Therefore, in Table 8, we conducted a

Table 8 Correlation matrix of total innovation performance with KPP&KCP

	KPP efficiency score	KCP efficiency score	Total efficiency score
KPP efficiency score	1	0.105	0.337
KCP efficiency score	0.105	1	0.590**
Total efficiency score	0.337	0.590**	1

***, **, * represent significance at 1, 5 and 10% level of significance, respectively

correlation analysis between the total efficiency score and the two other sub-processes scores.

Table 8 shows that the total innovation performance of studied NISs depends more on the commercialization process of scientific and technical knowledge than on the knowledge production process. The correlation matrix also shows that there is a relationship between the total innovation performance and the KPP performance; however, this relationship is not significant enough to claim a causal relationship between these two processes.

Table 8 also shows that the relationship between KPP efficiency score and KCP efficiency score is positive but insignificant. Besides, results in Table 6 show that in most of the studied NISs the performance of KPP is better than the performance of KCP. This means that at some point, any increase in investments in KPP would cause a decrease in the KCP performance. All BRICS economies are good cases of such phenomenon. This result confirms our choice of the input-oriented model for the knowledge production process, as efficiently managing the inputs of this process would reduce the opportunity cost of investing in commercial exploitation of knowledge at the national level.

Considering that all BRICS economies have low performance in commercializing their scientific and technical knowledge. It is important to mention that improving the commercialization of scientific and technical knowledge alone will not improve the national innovation performance of the BRICS countries, where innovation is not only technical know-how but also a socio-economic phenomenon. In this context, it is worth noting that most BRICS countries lack a national innovation paradigm. Previous studies (Miravitlles et al., 2017; Wang & Li-Ying, 2014) have shown that these countries tend to imitate foreign technological models rather than developing a local model based on local capabilities. In addition, most of BRICS countries suffer from the problem of translating technological developments into improvements in social and economic conditions. This makes governments lack the resources, expertise and legitimacy to develop a national innovation industrial behaviour.

Limitations

The introduced framework analysis of DEA is a one-way path, where it does not consider the other innovation channels that contribute to the national innovation performance such as social innovation and the spillovers of other innovation agents' interactions. Moreover, we think that studying the impact of the political economy related factors such as political system, and corruption on the total performance of innovation system would provide a different research perspective in the innovation studies. So, considering these other research aspects of innovation system in future studies is a good scope for other scholars to study.

Conclusion

In this study, an assessment of the BRICS NISs was conducted based on a bias-corrected network DEA. The national innovation process of NIS was divided into two sub-processes: knowledge production process and knowledge commercialization process. In doing so, we have bridged the research gap in the existing literature that used to deal with the innovation system as a one process leading to misleading results.

The results showed that BRICS NISs suffer from low performance in commercializing their outputs of universities and research organizations. On the other hand, their performance in creating scientific and technical knowledge is good in comparison to other studied countries. We suggest that the reason behind this imbalance is the network system failure associated with weak institutions and high uncertainty in the economy.

Moreover, based on the projection analysis and correlation matrix analysis of DEA results, we suggest that in order to improve the national innovation performance of the BRICS countries, they need to do the following measures:

A. Shrinking the investment in the KPP inputs and focusing on adopting new management methods that reduce the cost opportunity of investing in the KCP.
B. Building enablers and bridging organizations with a good institutional framework is a prerequisite of an efficient and productive relationship between the main NIS's actors.
C. A strong presence of government as a coordinator and a rules-maker at the national level is needed in BRICS economies that have a long history and experience in central planning.
D. Economic openness, well-structured and equipped technology clusters and clear definition of intellectual property rights are decisive elements in stimulating national and foreign investment and building sound industrial policy. With these conditions, MNCs will have the incentive to launch innovation-related businesses in BRICS countries. Consequently, the local industry will be able to absorb advanced technology and practices through interactive learning.
E. Building an international science, technology and innovation (STI) collaboration framework among BRICS countries helps in (1) accessing to advanced scientific and technical knowledge, (2) faster exchanging and transferring knowledge and practices and (3) developing human resources in the field of science and technology (Sokolov et al., 2019).

All the above measures are directed at improving the performance of the commercialization process of knowledge in BRICS economies in order to improve their NISs. However, we argue that building a good NIS does not necessarily mean improving the national economic and social conditions automatically, evidence from the Indian case support this argument. Technological developments must be translated into improvements in the standard of living of citizens and lead to building a free and open knowledge society, which is an important prerequisite for sustaining innovation-based economic growth. Finally, we suggest that studying the political economy of the innovation system in the future studies will provide more insights to the policymakers. So, they will be able to understand the interactions among the actors in the system and direct their innovation policies and strategies towards establishing highly synergetic relationships and more efficient innovative activities.

Appendix

Table 9 The dataset of study

DMU	GERD Fin Gov (Billions $)	Res Tot	GERD Perf Educ (Billions $)	S&T articl	Pat Appl	GERD Perf Bus (Billions $)	HiTech Exp (Billions $)	TM Appl (Thousands)
RU	12.15095	3898719	0.444865	53061	29269	23.99123	430	65.822
CN	58.56399	25572594	1.52428	411268	968252	314.5226	2580	2104.409
IND	26.37752	1982760	0.282994	106663	12579	21.90913	443	296.302
BRA	2.009318	2002760	0.142	53492	4641	2.476031	236	166.368
ZAF	1.159318	1408722	0.023346	11418	889	2.276031	105	37.976
AUT	2.282174	3089703	0.041595	12937	2205	9.291896	220	8.179
BEL	1.017636	2502906	0.04688	16852	949	9.090747	418	24.326
CAN	2.368248	10401526	0.15919	60496	4277	12.84176	563	54.665
DNK	0.180815	2643530	0.041409	14053	1462	5.271776	196	4.346
FIN	0.621866	1644946	0.038281	10753	1289	4.478563	102	4.819
FRA	7.663152	12289468	0.267308	72224	14306	39.62664	934	91.781
DEU	16.34186	19476501	0.351923	105755	47384	76.4126	1790	73.398
ITA	4.029964	8612910	0.118183	70814	8848	16.65911	608	41.849
KOR	8.20971	6624986	0.345463	64523	167275	57.53888	664	181.869
NLD	1.961899	5318467	0.076229	31069	2207	9.404093	906	21.56
NOR	0.88237	1797377	0.029237	10471	1153	3.382067	188	16.092
POL	2.202526	2681455	0.078622	32767	4676	4.772837	249	16.984
PRT	0.242278	1763855	0.038155	14582	925	1.849197	91.482	18.686
SGP	1.147866	2761579	0.036666	11221	1469	6.158726	591	22.74
ESP	3.636979	5445093	0.122235	54794	2799	10.37622	454	54.731
SWE	0.530779	4104273	0.066643	20669	2038	10.63594	273	10.498
TUR	1.486348	6216531	0.089657	33113	5352	7.634829	203	108.313
UK	3.210093	11395384	0.276584	101407	14867	30.42927	997	67.035
USA	54.103	64796000	1.351903	429139	288335	359.652	3050	393.21

Table 10 NIS-related DEA studies

Article	Method	Variables	
		Inputs	**Outputs**
Matei & Aldea, 2012	DEA Innovation leaders; Innovation followers; Moderate innovators; Modest innovators	• New doctorate graduates (ISCED 6) per 1000 population. • International scientific co-publications per million population. • Public R&D expenditures as % of GDP. • Business R&D expenditures as % of GDP. • patents applications per billion GDP. trademarks per billion GDP • Trademarks per billion GDP.	• Employment in knowledge-intensive activities (manufacturing and services) as % of total employment. • Medium and high-tech product exports as % total product exports. • Knowledge-intensive services exports as % total service exports.
Guan & Chen, 2010	CRS- output oriented Two stages DEA process	• R&D expenditure. • Technology import.	• Patent applications. • High-tech export.
Lee & Park, 2005	DEA The output oriented CCR model + Clustering + Anova—ANOVA and Post-hoc Comparisons inventors, merchandisers, academicians, and duds	• R&D expenditure. • Average number of researchers.	• Technology balance of receipts. • Number of scientific and technical journal articles. • Number of triadic patent families.
Guan & Chen, 2012	DEA CRS and VRS, Network (2-stage)-output oriented Super efficiency + Tobit regression on environmental factors	• Number of full-time equivalent scientists and engineers. • Incremental R&D expenditure funding. • Innovation activities. • Prior accumulated knowledge stock breeding upstream knowledge production. • Consumed full-time equivalent labour for non-R&D activities. • Number of patents granted.	• Number of patents granted. • International scientific papers. • Added value of industries. • Export of new products in high-tech industries.
Lu et al., 2014	Network DEA	• Total R&D personnel. • Public expenditures on education. • Import of goods and commercial services. • Total expenditures on R&D.	• GDP • Published scientific articles. • Patents (residents and nonresidents).
Carayannis et al., 2015	VRS-multistage, multilevel (2 stages x 2 levels)	• Science graduates in tertiary education. • Participation in lifelong learning. • Total R&D expenditure. • R&D capital stock. • Citable documents. • Patent applications. • Employment in knowledge intensive services/manufacturing. • SMEs collaborating with others. • Venture capital investment.	• High Tech Exports. • Sales of new to market and new to firm innovation. • License and patent revenues from abroad. • Number of trademark applications in national offices.
Wang &	Three-stage approach	• GERD.	• Patents.

Table 10 NIS-related DEA studies *(Continued)*

Article	Method	Variables	
		Inputs	**Outputs**
Huang, 2007	Input-oriented DEA – BCC; Tobit regressions; Parameter estimates from the second stage are used to predict the total input slacks.	• Fixed capital formation. • Researchers. • Technicians	• SCI Papers. • EI Papers.
Chen et al., 2011	DEA–output-oriented- CRS	• Total R&D manpower. • R&D expenditure stocks.	• Patents. • Scientific journal articles. • Royalty and licensing fees.
Pan et al., 2010	Input- oriented DEA model	• Total public expenditure on education. • Imports of goods and commercial services. • Total expenditure on R&D. • Direct investment stocks abroad. • Total R&D personnel nationwide.	• Number of patents granted to residents. • Number of patents secured abroad by national residents. • Scientific articles published by origin of author.
Cai, 2011	DEA + OLS Regression	• R&D expenditure as a % of GDP. • Total R&D personnel.	• Patents per 1000 population. • Scientific articles per 1000 population. • High-tech exports as a % of total manufacturing exports.
Afzal, 2014	Output- oriented DEA- CRS + Tobit regression model	• Population ages 15 to 65 (% of total) as labour force. • Computer users per 1000. • Domestic credit provided by banking sector (% of GDP). • R&D expenditure % GDP. • School enrolment, secondary (%gross). • Cost of business start-up procedure (% of GNI per capita). • Regulatory quality. • Openness (Trade (% of GDP). • Total natural resources rents (% of GDP).	• High-tech export as % total manufacturing exports.
Jon M. Zabala-Iturriagagoitia et al., 2007	DEA	• Property right; medium-tech industries. • Public R&D expenditure R&D. • Business R&D expenditure. • The percentage of the population between 25 and 64 years of age with a higher education	• Patents. • GDP per capita.
Kou et al., 2016	Multi-period and multi-division systems (MPMDS), Dynamic network DEA (DN–DEA)	• R&D expenditure. • R&D personnel. • S&T papers. • Technology import.	• Export of high -tech products. • GDP of employment (The ratio of gross domestic product (GDP) to total employment in the economy).
Nasierowski & Arcelus, 2003	Two step- DEA (CCR) input-orientation + PCA (two principal components analysis)	• Imports of goods and commercial services. • Gross domestic expenditure on research. • Employment in R&D. • Total educational expenditures.	• External patents by resident. • Patents by a country's residents. • National productivity.
Furman et al.,	Modeling national innovative	• Patents.	• Publications.

Table 10 NIS-related DEA studies *(Continued)*

Article	Method	Variables	
		Inputs	**Outputs**
2002	capacity based on Romer formulation	• Patent per million. • R&D expenditure. • Openness. • Education expenditure. • R&D spending by private sector. • R&D spending by Universities.	• GDP. • Capital Stock. • High-tech exports.
Crespo & Crespo, 2016	Fuzzy-set qualitative comparative analysis.	• Institutions. • Human capital and research. • Infrastructure. • Market sophistication. • Business sophistication.	
Filippetti & Peyrache, 2011	DEA and PCA	• Triadic patents. • Business R&D (BERD). • Total researchers in R&D (FTE). • Scientific and technical articles. • Public R&D. • Higher Education Expenditure on R&D. • Labour force with tertiary education.	
Zhao et al., 2015	Ordinal Multidimensional Scaling and Cluster analysis	–	
Wang, Zhao, & Zhang, 2016	The time lags effects of innovation input on output in the NISs	• Researchers in R&D (per million people). • R&D expenditure (% of GDP). • Regulatory quality. • University-industry research collaboration. • Patent applications, residents.	
Sesay et al., 2018	Dynamic Panel Data Analysis NIS ➔ Economic Growth	• University enrolment rate for science and engineering students. • government research and development expenditure. • High-tech export. • Total number of patents. • Scientific personnel. • Scientific and technical journal articles. • Economic freedom.	
Proksch et al., 2017	Fuzzy-set qualitative comparative analysis (fsQCA)	• International patents per million inhabitants. • GDP per capita. • Stock of international patents. • Aggregate R&D expenditures. • Openness. • Strength of protection for IP. • Share of government expenditure on higher education. • Stringency of antitrust policies. • Specialization degree. • New business registered. • Capital formation.	
Pires & Garcia, 2012	Stochastic Frontier Analysis (SFA) productivity analysis	• GDP growth. • Capital accumulation. • Labour expansion. • Change in GDP per worker. • R&D expenditures. • Average years of schooling of population over 25 years.	
Ivanova et al., 2017	Economic complexity index; Patent complexity index; Triple-helix complexity index	Patent and groups of products.	
Altuntas et al., 2016	A fuzzy-logic based data-mining approach to assess innovation capability of manufacturing systems	–	
Samara et al., 2012	The paper analyses the impact of innovation Policies on the NIS performance based on system	• Public Expenditure on R&D. • Private Expenditures on R&D. • Patent.	

Table 10 NIS-related DEA studies *(Continued)*

Article	Method	Variables	
		Inputs	Outputs
	dynamics (SD)	• Trademark. • Total public education expenditure. • Population with tertiary education per 100 population aged. • Doctorate graduates per 1000 population aged. • Government debt (% GDP). • Total tax rate. • Number of procedures required to start a business. • Venture capital. • Employment in knowledge intensive services (% of workforce).	

Acknowledgements
Not applicable.

Author's contributions
AI performed the DEA analysis of the BRICS countries and wrote all parts of the study. All authors read and approved the final manuscript.

Funding
The authors received no financial support for the research, authorship, and/or publication of this article.

Availability of data and materials
The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no conflict of interest.

Received: 29 October 2020 Accepted: 25 March 2021
Published online: 12 July 2021

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. https://doi.org/10.1386/tmsd.9.3.195_1.

Afzal, M. N. I. (2014). An empirical investigation of the National Innovation System (NIS) using Data Envelopment Analysis (DEA) and the TOBIT model. *International Review of Applied Economics*, *28*(4), 507–523. https://doi.org/10.1080/02692171.2014.896880.

Allard, G., Martinez, C. A., & Williams, C. (2012). Political instability, pro-business market reforms and their impacts on national systems of innovation. *Research Policy*, *41*(3), 638–651. https://doi.org/10.1016/j.respol.2011.12.005.

Alnafrah, I. (2019). Dynamic structural comparison of BRICS national innovation systems based on machine learning techniques. *International Journal of Technological Learning, Innovation and Development*, *11*(3), 265–290. https://doi.org/10.1504/IJTLID.2019.102681.

Alnafrah, I., Al Naimi, K., & Ahmad, M. (2018). A comparative analysis of national innovation systems' structures and their developmental impacts (Evidences from BRICS countries). *Economics and Environmental Management*, *1*(32), 13–20. https://doi.org/10.17586/2310-1172-2018-11-1-13-20.

Alnafrah, I., & Bogdanova, E. (2018). National innovation system and its role in increasing GDP per capita (Evidence from Russia). *Journal of Economic Regulation*, *9*(1), 33–39.

Alnafrah, I., & Zeno, B. (2019). A new comparative model for national innovation systems based on machine learning classification techniques. *Innovation and Development*, *10*(1), 45–66. https://doi.org/10.1080/2157930x.2018.1564124.

Altuntas, S., Dereli, T., & Kusiak, A. (2016). Assessment of corporate innovation capability with a data-mining approach: industrial case studies. *Computers & Industrial Engineering*, *102*, 58–68. https://doi.org/10.1016/J.CIE.2016.10.018.

Andersen, P. D., Andersen, A. D., Jensen, P. A., & Rasmussen, B. (2014). Sectoral innovation system foresight in practice: Nordic facilities management foresight. *Futures*, *61*, 33–44. https://doi.org/10.1016/j.futures.2014.04.012.

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://doi.org/10.1287/mnsc.30.9.1078.

Biryukova, O. V., & Matiukhina, A. I. (2019). ICT services trade in the BRICS countries: Special and common features. *Journal of the Knowledge Economy*, *10*(3), 1080–1097. https://doi.org/10.1007/s13132-017-0517-6.

Brando Santana, N., Mariano, E. B., Camioto, F. d. C., & Rebelatto, D. A. d. N. (2015). National innovative capacity as determinant in sustainable development: a comparison between the BRICS and G7 countries. *International Journal of Innovation and Sustainable Development*, *9*(3/4), 384. https://doi.org/10.1504/IJISD.2015.071860.

Cai, Y. (2011). Factors affecting the efficiency of the BRICSs' national innovation systems: a comparative study based on dea and panel data analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1974368.

Cai, Y., & Hanley, A. (2012). *Building BRICS: 2-stage DEA analysis of R&D efficiency (issue 1788).*

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://doi.org/10.1007/s12351-015-0176-y.

Carayannis, E. G., Grigoroudis, E., & Goletsis, Y. (2016). A multilevel and multistage efficiency evaluation of innovation systems: A multiobjective DEA approach. *Expert Systems with Applications*, *62*(15 November), 63–80. https://doi.org/10.1016/j.eswa.2016.06.017.

Cassiolato, J. E., & Vitorino, V. (2009). BRICS and development alternatives: Innovation systems and policies. In *BRICS and development alternatives: Innovation systems and policies*. https://doi.org/10.7135/UPO9781843318149.

Castellacci, F., & Natera, J. M. (2013). The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity. *Research Policy*, *42*(3), 579–594. https://doi.org/10.1016/j.respol.2012.10.006.

Charnes, A., Cooper, W., Golany, B., Seiford, L., & Stutz, J. (1985). Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *Journal of Econometrics*, *30*(1–2), 91–107. https://doi.org/10.1016/0304-4076(85)90133-2.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8.

Chen, C.-P., Hu, J.-L., & Yang, C.-H. (2011). An international comparison of R&D efficiency of multiple innovative outputs: The role of the national innovation system. *Innovation*, *13*(3), 341–360. https://doi.org/10.5172/impp.2011.13.3.341.

Chen, K., & Guan, I. (2011). Mapping the innovation production process from accumulative advantage to economic outcomes: A path modeling approach. *Technovation*, *31*(7), 336–346. https://doi.org/10.1016/j.technovation.2011.03.004.

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://doi.org/10.1080/00343404.2010.497479.

Chen, K., Kou, M., & Fu, X. (2018). Evaluation of multi-period regional R&D efficiency: An application of dynamic DEA to China's regional R&D systems. *Omega*, *74*, 103–114. https://doi.org/10.1016/J.OMEGA.2017.01.010.

Chen, Y., Cook, W. D., Li, N., & Zhu, J. (2009). Additive efficiency decomposition in two-stage DEA. *European Journal of Operational Research*, *196*(3), 1170–1176. https://doi.org/10.1016/j.ejor.2008.05.011.

Chung, S. (2002). Building a national innovation system through regional innovation systems. *Technovation*, *22*(8), 485–491. https://doi.org/10.1016/S0166-4972(01)00035-9.

Cook, W. D., Liang, L., & Zhu, J. (2010). Measuring performance of two-stage network structures by DEA: A review and future perspective. *Omega*, *38*(6), 423–430. https://doi.org/10.1016/J.OMEGA.2009.12.001.

Cooper, W. W., Seiford, L. M., & Tone, K. (2006). Introduction to data envelopment analysis and its uses: With DEA-solver software and references. In *Introduction to data envelopment analysis and its uses: With DEA-solver software and references*. https://doi.org/10.1007/0-387-29122-9.

Crespo, N. F., & Crespo, C. F. (2016). Global innovation index: Moving beyond the absolute value of ranking with a fuzzy-set analysis. *Journal of Business Research*, *69*(11), 5265–5271. https://doi.org/10.1016/J.JBUSRES.2016.04.123.

Cron, W. L., & Sobol, M. G. (1983). The relationship between computerization and performance: A strategy for maximizing the economic benefits of computerization. *Information & Management*, *6*(3), 171–181. https://doi.org/10.1016/0378-7206(83)90034-4.

Didenko, A., Loseva, O., & Abdikeev, N. (2017). Measuring efficiency of regional innovation system with DEA and PCA. In *2017 IEEE 11th International Conference on Application of Information and Communication Technologies (AICT)*, (pp. 1–4). https://doi.org/10.1109/ICAICT.2017.8687279.

Distefano, F., Gambillara, G., & Di Minin, A. (2016). Extending the innovation paradigm: A double 'I' environment and some evidence from BRIC countries. *Journal of the Knowledge Economy*, *7*(1), 126–154. https://doi.org/10.1007/s13132-015-0299-7.

Edquist, C. (2009). Systems of innovation: Perspectives and challenges. In *The Oxford handbook of innovation*. https://doi.org/10.1093/oxfordhb/9780199286805.003.0007.

Emrouznejad, A., & Yang, G. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*, *61*, 4–8. https://doi.org/10.1016/J.SEPS.2017.01.008.

Fagerberg, J., Mowery, D. C., & Verspagen, B. (2009). The evolution of Norway's national innovation system. *Science and Public Policy*, *36*(6), 431–444. https://doi.org/10.3152/030234209X460944.

Färe, R., & Grosskopf, S. (2000). Network DEA. *Socio-Economic Planning Sciences*, *34*(1), 35–49. https://doi.org/10.1016/S0038-0121(99)00012-9.

Filippetti, A., & Peyrache, A. (2011). The patterns of technological capabilities of countries: A dual approach using composite indicators and data envelopment analysis. *World Development*, *39*(7), 1108–1121. https://doi.org/10.1016/J.WORLDDEV.2010.12.009.

Freeman, C. (1982). *The economics of industrial innovation*. MIT Press.

Freeman, C., & Lundvall, B.-A. (1988). *Small countries facing the technological revolution*. Pinter https://vbn.aau.dk/en/publications/small-countries-facing-the-technological-revolution.

Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. *Research Policy*, *31*(6), 899–933. https://doi.org/10.1016/S0048-7333(01)00152-4.

Gao, X., & Yuan, J. (2020). Policymaking challenges in complex systems: The political and socio-technical dynamics of solar photovoltaic technology deployment in China. *Energy Research and Social Science*, *64*, 101426. https://doi.org/10.1016/j.erss.2020.101426.

Godin, B. (2009). National innovation system: The system approach in historical perspective. *Science, Technology, & Human Values*, *34*, 476–501. Sage Publications, Inc. https://doi.org/10.2307/27786171.

Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega*, *17*(3), 237–250. https://doi.org/10.1016/0305-0483(89)90029-7.

Grupp, H., & Schubert, T. (2010). Review and new evidence on composite innovation indicators for evaluating national performance. *Research Policy*, *39*(1), 67–78. https://doi.org/10.1016/j.respol.2009.10.002.

Guan, J., & Chen, K. (2010). Measuring the innovation production process: A cross-region empirical study of China's high-tech innovations. *Technovation*, *30*(5–6), 348–358. https://doi.org/10.1016/j.technovation.2010.02.001.

Guan, J., & Chen, K. (2012). Modeling the relative efficiency of national innovation systems. *Research Policy*, *41*(1), 102–115. https://doi.org/10.1016/j.respol.2011.07.001.
Hekkert, M. P., Suurs, R. A. A., Negro, S. O., Kuhlmann, S., & Smits, R. E. H. M. (2007). Functions of innovation systems: A new approach for analysing technological change. *Technological Forecasting and Social Change*, *74*(4), 413–432. https://doi.org/10.1016/J.TECHFORE.2006.03.002.
Huang, W., & Eling, M. (2013). An efficiency comparison of the non-life insurance industry in the BRIC countries. *European Journal of Operational Research*, *226*(3), 577–591. https://doi.org/10.1016/j.ejor.2012.11.008.
Hudec, O., & Prochádzková, M. (2013). The relative efficiency of knowledge innovation processes in EU countries. *Studies in Regional Science*, *41*(1), 145–162. https://doi.org/10.2457/srs.43.145.
Ivanova, I., Strand, Ø., Kushnir, D., & Leydesdorff, L. (2017). Economic and technological complexity: A model study of indicators of knowledge-based innovation systems. *Technological Forecasting and Social Change*, *120*(July 2017), 77–89. https://doi.org/10.1016/j.techfore.2017.04.007.
Jiménez-Sáez, F., Zabala-Iturriagagoitia, J. M., Zofío, J. L., & Castro-Martínez, E. (2011). Evaluating research efficiency within National R&D Programmes. *Research Policy*, *40*(2), 230–241. https://doi.org/10.1016/J.RESPOL.2010.10.005.
Kao, C. (2014). Network data envelopment analysis: A review. *European Journal of Operational Research*, *239*(1), 1–16. https://doi.org/10.1016/J.EJOR.2014.02.039.
Kao, C., & Hwang, S.-N. (2008). Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. *European Journal of Operational Research*, *185*(1), 418–429. https://doi.org/10.1016/J.EJOR.2006.11.041.
Kao, C., & Hwang, S.-N. (2010). Efficiency measurement for network systems: IT impact on firm performance. *Decision Support Systems*, *48*(3), 437–446. https://doi.org/10.1016/j.dss.2009.06.002.
Klein Woolthuis, R., Lankhuizen, M., & Gilsing, V. (2005). A system failure framework for innovation policy design. *Technovation*, *25*(6), 609–619. https://doi.org/10.1016/J.TECHNOVATION.2003.11.002.
Kneip, A., Simar, L., & Wilson, P. W. (2011). A computationally efficient, consistent bootstrap for inference with non-parametric DEA estimators. *Computational Economics*, *38*(4), 483–515. https://doi.org/10.1007/s10614-010-9217-z.
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. https://doi.org/10.1016/J.ESWA.2015.10.032.
Krasikova, T. Y., & Ognev, D. V. (2014). Corruption as a negative factor affecting the development of university as a core in regional innovation system. *Actual Problems of Economics*, *161*(11), 161–165.
Kravtsova, V., & Radosevic, S. (2012). Are systems of innovation in Eastern Europe efficient? *Economic Systems*, *36*(1), 109–126. https://doi.org/10.1016/J.ECOSYS.2011.04.005.
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. https://doi.org/10.1080/19761597.2005.9668614.
Lengyel, B., & Leydesdorff, L. (2011). Regional innovation systems in Hungary: The failing synergy at the national level. *Regional Studies*, *45*(5), 677–693. https://doi.org/10.1080/00343401003614274.
Li, L., Dai, Q., Huang, H., & Wang, S. (2016). Efficiency decomposition with shared inputs and outputs in two-stage DEA. *Journal of Systems Science and Systems Engineering*, *25*(1), 23–38. https://doi.org/10.1007/s11518-016-5298-0.
Liou, D.-Y. (2009). Two-stage R&D efficiency evaluation from the perspective of national innovation system. In *PICMET '09 - 2009 Portland International Conference on Management of Engineering & Technology*, (pp. 180–186). https://doi.org/10.1109/PICMET.2009.5262226.
Liu, X., & White, S. (2001). Comparing innovation systems: a framework and application to China's transitional context. *Research Policy*, *30*(7), 1091–1114. https://doi.org/10.1016/S0048-7333(00)00132-3.
Liu, Z., Chen, X., Chu, J., & Zhu, Q. (2018). Industrial development environment and innovation efficiency of high-tech industry: analysis based on the framework of innovation systems. *Technology Analysis & Strategic Management*, *30*(4), 434–446. https://doi.org/10.1080/09537325.2017.1337092.
Lobazova, O. F. (2019). Mentality as a factor of innovation and anti-corruption behavior in the social management system. *International Journal of Innovative Technology and Exploring Engineering*, *8*(12), 4667–4672. https://doi.org/10.35940/ijitee.L3867.1081219.
Lu, W.-M., Kweh, Q. L., & Huang, C.-L. (2014). Intellectual capital and national innovation systems performance. *Knowledge-Based Systems*, *71*, –210. https://doi.org/10.1016/j.knosys.2014.08.001.
Lundvall, B. Å. (2007). National innovation systems—Analytical concept and development tool. *Industry and Innovation*, *14*(1), 95–119. https://doi.org/10.1080/13662710601130863.
Malerba, F. (2002). Sectoral systems of innovation and production. *Research Policy*, *31*(2), 247–264. https://doi.org/10.1016/S0048-7333(01)00139-1 http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.323.6486&rep=rep1&type=pdf.
Matei, M. M., & Aldea, A. (2012). Ranking national innovation systems according to their technical efficiency. *Procedia - Social and Behavioral Sciences*, *62*(24 October), 968–974. https://doi.org/10.1016/j.sbspro.2012.09.165.
Meng, W., Hu, Z., & Liu, W. (2006). Efficiency evaluation of basic research in China. *Scientometrics*, *69*(1), 85–101. https://doi.org/10.1007/s11192-006-0140-y.
Metcalfe, S., & Ramlogan, R. (2008). Innovation systems and the competitive process in developing economies. *The Quarterly Review of Economics and Finance*, *48*(2), 433–446. https://doi.org/10.1016/j.qref.2006.12.021.
Miravitlles, P., Achcaoucaou, F., Núñez-Carballosa, A., Guitart-Tarrés, L., & Cruz-Cazares, C. (2017). Are the BRIC countries overtaking intermediate countries in the race for international R&D? The case of Spain. *Technology Analysis & Strategic Management*, *29*(6), 672–686. https://doi.org/10.1080/09537325.2016.1227063.
Namazi, M., & Mohammadi, E. (2018). Natural resource dependence and economic growth: A TOPSIS/DEA analysis of innovation efficiency. *Resources Policy*, *59*, 544–552. https://doi.org/10.1016/J.RESOURPOL.2018.09.015.
Nasierowski, W., & Arcelus, F. J. (2003). On the efficiency of national innovation systems. *Socio-Economic Planning Sciences*, *37*(3), 215–234. https://doi.org/10.1016/S0038-0121(02)00046-0.
Nelson, R. R. (1993). *National innovation systems: A comparative analysis*. Oxford University Press.
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. https://doi.org/10.1142/S0217595910002752.

Papaioannou, T., Watkins, A., Mugwagwa, J., & Kale, D. (2016). To lobby or to partner? Investigating the shifting political strategies of biopharmaceutical industry associations in innovation systems of South Africa and India. *World Development*, *78*, 66–79. https://doi.org/10.1016/j.worlddev.2015.10.017.

Pertuze Salas, J., Reyes, T., Vassolo, R. S., & Olivares, N. (2019). Political uncertainty and innovation: The relative effects of national leaders' education levels and regime systems on firm-level patent applications. *Research Policy*, *48*(9), 103808. https://doi.org/10.1016/j.respol.2019.103808.

Pires, J. O., & Garcia, F. (2012). Productivity of nations: A stochastic frontier approach to TFP decomposition. *Economics Research International*, *2012*, 1–19. https://doi.org/10.1155/2012/584869.

Proksch, D., Haberstroh, M. M., & Pinkwart, A. (2017). Increasing the national innovative capacity: Identifying the pathways to success using a comparative method. *Technological Forecasting and Social Change*, *116*(March), 256–270. https://doi.org/10.1016/j.techfore.2016.10.009.

Ramanathan, R., Ramanathan, U., & Bentley, Y. (2018). The debate on flexibility of environmental regulations, innovation capabilities and financial performance—A novel use of DEA. *Omega*, *75*, 131–138. https://doi.org/10.1016/J.OMEGA.2017.02.006.

Rao-Nicholson, R., Vorley, T., & Khan, Z. (2017). Social innovation in emerging economies: A national systems of innovation based approach. *Technological Forecasting and Social Change*, *121*, 228–237. https://doi.org/10.1016/j.techfore.2017.03.013.

Rousseau, S., & Rousseau, R. (1997). Data envelopment analysis as a tool for constructing scientometric indicators. *Scientometrics*, *40*(1), 45–56. https://doi.org/10.1007/BF02459261.

Samara, E., Georgiadis, P., & Bakouros, I. (2012). The impact of innovation policies on the performance of national innovation systems: A system dynamics analysis. *Technovation*, *32*(11), 624–638. https://doi.org/10.1016/J.TECHNOVATION.2012.06.002.

Scerri, M., Clara Couto Soares, M., & Maharajh, R. (2010). *Comparative report on innovation systems and inequality in the BRICS. From the research project: National Innovation Systems of BRICS countries. (IDRC Center file 104227-001)*.

Scerri, M., & Lastres, H. M. (2013). The state and the architecture of national systems of innovation. In M. Scerri, & H. M. M. Lastres (Eds.), *The role of the state*, (pp. 1–21). Routledge India.

Sesay, B., Yulin, Z., & Wang, F. (2018). Does the national innovation system spur economic growth in Brazil, Russia, India, China and South Africa economies? Evidence from panel data. *South African Journal of Economic and Management Sciences*, *21*(1), 1–12. https://doi.org/10.4102/sajems.v21i1.1647.

Sharma, S., & Thomas, V. J. (2008). Inter-country R&D efficiency analysis: An application of data envelopment analysis. *Scientometrics*, *76*(3), 483–501. https://doi.org/10.1007/s11192-007-1896-4.

Simar, L., & Wilson, P. (1998). Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Management Science*, *44*(1), 49–61. https://doi.org/10.1287/mnsc.44.1.49.

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://doi.org/10.1016/j.jeconom.2005.07.009.

Sokolov, A., Shashnov, S., Kotsemir, M., & Grebenyuk, A. (2019). Quantitative analysis for a better-focused international STI collaboration policy: A case of BRICS. *Technological Forecasting and Social Change*, *147*, 221–242. https://doi.org/10.1016/J.TECHFORE.2019.07.008.

Song, M. L., Zhang, L. L., Liu, W., & Fisher, R. (2013). Bootstrap-DEA analysis of BRICS' energy efficiency based on small sample data. *Applied Energy*, *112*, 1049–1055. https://doi.org/10.1016/j.apenergy.2013.02.064.

Tarnawska, K., & Mavroeidis, V. (2015). Efficiency of the knowledge triangle policy in the EU member states: DEA approach. *Triple Helix*, *2*(1), 1–22. https://doi.org/10.1186/s40604-015-0028-z.

Tseng, C.-Y. (2009). Technological Innovation in The Bric Economies. *Research-Technology Management*, *52*(2), 29–35. https://doi.org/10.1080/08956308.2009.11657556.

Tsolas, I. E. (2011). Performance assessment of mining operations using nonparametric production analysis: A bootstrapping approach in DEA Ioannis. *Resources Policy*, *36*(2), 159–167. https://doi.org/10.1016/j.resourpol.2010.10.003.

Tu, C. J., Chang, M. C., & Chen, C. P. (2016). Progressive time-weighted dynamic energy efficiency, energy decoupling rate, and decarbonization: An empirical study on G7 and BRICS. *Sustainability (Switzerland)*, *8*(9). https://doi.org/10.3390/su8090928.

Viotti, E. B. (2002). National Learning Systems: A new approach on technological change in late industrializing economies and evidences from the cases of Brazil and South Korea. *Technological Forecasting and Social Change*, *69*(7), 653–680. https://doi.org/10.1016/S0040-1625(01)00167-6.

Wang, C., Gopal, R. D., & Zionts, S. (1997). Use of data envelopment analysis in assessing information technology impact on firm performance. *Annals of Operations Research*, *73*(0), 191–213. https://doi.org/10.1023/A:1018977111455.

Wang, D., Zhao, X., & Zhang, Z. (2016). The time lags effects of innovation input on output in national innovation systems: The case of China. *Discrete Dynamics in Nature and Society*, *2016*, 1–12. https://doi.org/10.1155/2016/1963815.

Wang, E. C., & Huang, W. (2007). Relative efficiency of R&D activities: A cross-country study accounting for environmental factors in the DEA approach. *Research Policy*, *36*(2), 260–273. https://doi.org/10.1016/J.RESPOL.2006.11.004.

Wang, S., Fan, J., Zhao, D., & Wang, S. (2016). Regional innovation environment and innovation efficiency: the Chinese case. *Technology Analysis & Strategic Management*, *28*(4), 396–410. https://doi.org/10.1080/09537325.2015.1095291.

Wang, Y., & Li-Ying, J. (2014). How do the BRIC countries play their roles in the global innovation arena? A study based on USPTO patents during 1990–2009. *Scientometrics*, *98*(2), 1065–1083. https://doi.org/10.1007/s11192-013-1141-2.

Wang, Y.-M., & Chin, K.-S. (2010). Some alternative DEA models for two-stage process. *Expert Systems with Applications*, *37*(12), 8799–8808. https://doi.org/10.1016/J.ESWA.2010.06.024.

Watkins, A., Papaioannou, T., Mugwagwa, J., & Kale, D. (2015). National innovation systems and the intermediary role of industry associations in building institutional capacities for innovation in developing countries: A critical review of the literature. *Research Policy*, *44*(8), 1407–1418. https://doi.org/10.1016/j.respol.2015.05.004.

Yao, X., Watanabe, C., & Li, Y. (2009). Institutional structure of sustainable development in BRICs: Focusing on ICT utilization. *Technology in Society*, *31*(1), 9–28. https://doi.org/10.1016/J.TECHSOC.2008.10.013.

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. https://doi.org/10.1080/00343400601120270.

Zabala-Iturriagagoitia, J. M., Aparicio, J., Ortiz, L., Carayannis, E. G., & Grigoroudis, E. (2020). The productivity of national innovation systems in Europe: Catching up or falling behind? *Technovation*, 102215. https://doi.org/10.1016/j.technovation.2020.102215.

Zaichenko, S. (2014). National innovation system and inequality in Russia. In *Inequality and development challenges*, (pp. 80–148). Routledge. https://doi.org/10.4324/9781315734170-3.

Zemtsov, S., & Kotsemir, M. (2019). An assessment of regional innovation system efficiency in Russia: the application of the DEA approach. *Scientometrics*, *120*(2), 375–404. https://doi.org/10.1007/s11192-019-03130-y.

Zhao, S. L., Cacciolatti, L., Lee, S. H., & Song, W. (2015). Regional collaborations and indigenous innovation capabilities in China: A multivariate method for the analysis of regional innovation systems. *Technological Forecasting and Social Change*, *94*(May), 202–220. https://doi.org/10.1016/j.techfore.2014.09.014.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.