Science and Public Policy, 46(4), 2019, 530–540
doi: 10.1093/scipol/scz005
Advance Access Publication Date: 8 March 2019
Article

Assessing the efficiency of national innovation systems in developing countries

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Abstract

Despite the growing importance of developing countries to the global economy and their increasing role in innovation, limited academic attention has been given to the national innovation systems (NIS) of these countries. Given that they commonly suffer a lack of resources, efficiency in the operation of innovation seems crucial. This study aims to assess the innovation efficiency of developing countries. Breaking down the NIS into two stages, knowledge production and application process, we additionally introduce the knowledge absorption perspective in the latter stage as the consideration for the context of developing countries. Based on the results of the efficiency assessment, clustering analysis is implemented to identify several typologies of the operation of NIS in developing countries and to provide implications for each case. This study will constitute a meaningful attempt to provide a general understanding of innovation status and operations in developing countries, thereby suggesting policy directions for several cases.

Key words: national innovation system; innovation efficiency; developing countries; DEA; clustering

1. Introduction

Science, technology, and innovation (STI) has been recognised as a major tool for increasing national competitiveness and economic growth (Padilla-Pérez and Gaudin 2014). In fact, policies relevant to STI are often included in countries' development strategies. On a global level, STI is one of the pillars that comprise the United Nations 2030 Agenda for Sustainable Development. Among the frameworks that have drawn the attention of policymakers for national-level innovation is the national innovation systems (NIS) approach. As a lens to capture how well a country's NIS are performing from a systematic perspective, it has been widely utilised by international organisations, as well as country policymakers, for various policy purposes (Padilla-Pérez and Gaudin 2014). In particular, on adopting such a systematic approach, governments tend to focus on innovation efficiency and the effect of government intervention on such efficiency (Guan and Chen 2012).

However, relatively limited academic attention has been given to measuring innovation efficiency at the country level. Such omission can constitute a significant loss to ensure appropriate policy grounds to support the development of national innovation capabilities (Kontolaimou et al. 2016). Moreover, much literature that has examined innovation efficiency at the country level has been directed at advanced economies (see Section 2). Given the increasing importance of developing countries in the world economy, more focus on understanding their innovation systems would be meaningful. At the same time, countries aiming to improve policy learning to develop sound policy directions generally adopt 'best practices'. Thus, examining innovation efficiency across countries might be a useful and necessary step to identify benchmarks and discover areas of weakness (Guan and Chen 2012).

The main purpose of this study is to assess the innovation efficiency of developing countries. Based on previous studies, NIS is viewed as being largely composed of knowledge production process (KPP) and knowledge commercialisation or application process (KAP). We break down the NIS into two such stages. In addition, considering the characteristics of developing countries, an additional component, knowledge absorption, is incorporated as the other input for KAP. Based on this framework, relational network data envelopment analysis (DEA) (Kao 2009) was employed to analyse the relative efficiency of developing countries. Traditional DEA deals with a single process consisting of input and output relation. On the other hand, multi-stage DEA, wherein a two-stage approach is most common, attempts to unfold the 'black-box' inside the system by identifying component processes and clarifying the origin of inefficiencies. As one of the approaches to explain such multi-stage cases, we apply relational network DEA, which seems appropriate to describe our framework. We expect that two-stage-based analysis with relational network DEA will allow examining the internal operation of innovation investment and effort, while the introduction of knowledge absorption activities better describes the performance of NIS in a developing countries context.

Moreover, using the results of DEA analysis, clustering analysis was followed to classify the result into several typologies. Efficiency results are anticipated to elucidate the relative performance of KPP, KAP, and the system as a whole. Furthermore, we attempt to classify countries into several groups which have similar characteristics in NIS performance, so that each group can be given precise policy suggestions. Moreover, we specify each group based on its economic level, thereby suggesting more feasible targets for benchmarks in each case. Consideration of economic level is particularly critical for developing countries, which often suffer a lack of resources as compared to developed countries. In this sense, our analysis will provide insight for each country to learn how comparable are other countries, in terms of economic status, in making use of resources. It will also enable them to find and learn about countries that could be future targets when they enlarge the scale of NIS. In addition, such policy implications will be valuable to international organisations that seek efficient and effective allocation of resources for aid and international development.

The remainder of the article is organised as follows. Section 2 presents the literature review, and the research framework is introduced in Section 3. Section 4 describes the research method, and the results are reported in Section 5. Section 6 presents the implications, and Section 7 concludes.

2. Literature review

2.1 NIS

Innovation is regarded as the key driver for economic growth and national competitiveness (Hu and Mathews 2005). It seems a natural tendency that innovation is a top priority of policy agendas, both from industrial and regional development perspective (Tödtling and Trippl 2005). Traditionally, the so-called Schumpeterian view, represented by the linear model of innovation policy, was prevalent in the innovation field. However, an alternative perspective started to emerge. This perspective argues that innovation results not only from individual actors' performance, but also from how they interact with one another as parts of a system (Solleiro and Gaona 2012), that is, systems of innovation. The systems of innovation instead place emphasis on interaction between various actors involved in the innovation process. Innovation is an evolutionary and nonlinear process resulting from communication and collaboration between stakeholders (Tödtling and Trippl 2005). Thus, the reciprocal learning process across the national economy is regarded as a major driving force for long-term economic development (Fagerberg and Sapprasert 2011).

This concept was applied in several ways, such as in national, technological, and sectoral systems of innovation. As the initial application, the concept of NIS has emerged as a core objective of analysis in innovation process research since the mid-1980s (Diez and Kiese 2009). Since pioneered by Freeman (1987) and Lundvall (1985), NIS has been widely referred to in academic and practical contexts as a useful analytical tool, facilitating the understanding of processes and determinants of innovation (Guan and Chen 2012). Although initial work by Lundvall (1985) suggests a separate definition of a narrow and broad NIS, the broad definition is currently more generally used (Lundvall 2007). Thus, it embraces all activities and interaction between organisations and institutions involved in exploring, diffusing, absorbing, and using innovation (Marxt and Brunner 2013). Lundvall (2007) refers to this as a change from science or technology policy to innovation policy. This has accompanied increasing numbers of publications focusing on innovation policy, particularly using the NIS approach. According to NIS, innovation results from a complex interaction between actors who generate, diffuse, and apply a wide variety of knowledge. Thus, innovative achievements of a country largely depend on how these actors link with each other as components of a collective knowledge and technology creation systems (Pan et al. 2010).

2.2 Efficiency of NIS

Extant literature on NIS has encouraged policymakers to adopt systematic approaches other than linear thinking to national-level innovation. Following this line, governments began to pay attention to innovation efficiency, as well as to the effect of government intervention on innovation efficiency (Guan and Chen 2012). In this sense, various indicators have been developed and utilised to assess national innovation performance, such as patents and R&D activities. Cai (2011) identified three major quantitative methods in NIS research at the macro level: composite indicators, econometric approach, and DEA. While the former is mainly concerned with aggregating innovation-related indicators, econometric analysis primarily aims to determine factors that affect national innovation capacity (Carayannis et al. 2016). However, it is important to note that in today's highly competitive environments, countries implement a range of efforts for innovations, such as capital and human resources, to enhance operating performances. This has induced the focus of attention to shift from performance measurement with such single indicators to a multi-dimensional perspective (Pan et al. 2010). In fact, as Wennekers and Thurik (1999) asserted, innovation performance is affected not only by available resources, but also, and more importantly, by their efficient utilisation. In this sense, a number of works in the literature are concerned with national innovation or R&D efficiency. Within the context of NIS, investment in technology refers to inputs, thereby relating efficiency to the ability of NIS to alter R&D inputs into outputs (Nasierowski and Arcelus 2003). Thus, many previous studies tend to use either R&D (Chen et al. 2011; Cullmann et al. 2012; Lee and Park 2005; Sharma and Thomas 2008; Thomas et al. 2011; Wang 2007) or national innovation efficiency (Carayannis et al. 2016; Guan and Chen 2012; Kontolaimou et al. 2016; Kou et al. 2016; Liu et al. 2015; Lu et al. 2014; Nasierowski and Arcelus 2003; Pan et al. 2010) for the same meaning.

While some research examines national innovation efficiency holistically, others break it down into two stages. Guan and Chen (2012) proposed that knowledge innovation consists of KPP and knowledge commercialisation processes. They argued that process-oriented frameworks of NIS are necessary to measure innovation efficiency in order to determine what and how to improve innovation performance. In addition, the authors claimed that although innovative system approaches lead to nonlinear thinking, linear aspects remain dominant in the innovation's production perspective. In other words, these types of studies have called for a deeper investigation of how efficiently innovation resources are used in the entire innovation process. In fact, following Schumpeter's definition of innovation, numerous scholars have incorporated knowledge exploration (finding and developing) and exploitation (applying and commercialisation) stages (Carayannis et al. 2016). In this sense, a number of subsequent investigations have attempted to adopt this view and apply a similar approach, although the detailed structures of these studies vary. Lu et al. (2014) tested the R&D efficiency and economic efficiency of NIS, and, based on the results, examined how intellectual capital affects NIS performance. Liu et al. (2015) investigated the efficiency of NIS in the knowledge production and commercialisation process, and applied a network-based ranking method to model and compare the national characteristics of the countries analysed. Carayannis et al. (2016) implemented multi-level (national and regional) and multi-stage (knowledge production and commercialisation) efficiency of NIS, while Kou et al. (2016) measured multi-period efficiency in R&D and the application process.

3. Research framework

NIS essentially refers to the country's innovation effort, which is converted into economic development and productivity improvement, and ultimately fosters national competitiveness (Lu et al. 2014). The traditional one-stage DEA model does not take into account the internal operation of the innovation process, which refers to limitations in explicitly showing internal structure (Guan and Chen 2012). Since efficiency in knowledge production is not necessarily linked to efficiency in knowledge application, investigating different stages of the innovation process will provide more valuable insight for policy formation (Carayannis et al. 2016). The multi-stage model divides the whole process into several sub-processes, the output of the previous step being the input of the subsequent step. Most previous studies that examined the efficiency of NIS in the multi-stage context used two simplified stages: knowledge production, and knowledge commercialisation or application (Carayannis et al. 2016; Guan and Chen 2012; Kou et al. 2016; Liu et al. 2015). The KPP is defined as a process that comprises new knowledge upstream or generates knowledge outcomes by using research-related inputs. The latter stages, KAP, commercialise and apply new knowledge downstream by transforming the outcomes of the previous process into commercial and economic results. It should be noted that these two stages are interdependent because the outputs from the former process represent the inputs for the next process (Guan and Chen 2012).

Since this study focuses on developing countries, we propose adding one more construct to the intermediary input for the knowledge commercialisation process: knowledge absorption. Developing countries are generally recognised as having narrow and deficient domestic linkages, dualistic industry structure, and immature knowledge bases, and, thus, they might not possess an expansive base of local knowledge (Metcalfe and Ramlogan 2008). Given such a relatively weaker knowledge base of developing countries and their position of catching up to global technology leaders, knowledge acquisition from external sources might play a crucial role in creating innovation output. In fact, technology and knowledge transfer have long constituted central issues, particularly for developing countries that need to catch up to technology leaders, expecting that their acquisition and diffusion results in productivity growth which ultimately leads to economic development (Goodwin and Johnston 1999; Hoekman et al. 2005).

Trade and foreign direct investment (FDI) have been regarded as key channels through which technology dissemination occurs (Seck 2012). According to Criscuolo and Narula (2008)'s review, a substantial body of literature on R&D spillovers at the macro level has focused on spillovers through trade, while the literature at the micro level has mostly been concerned with spillovers from inward FDI. In fact, several studies have empirically examined knowledge spillovers via imports in developed countries, and most have found a significant impact on the level of total factor productivity of countries (Belitz and Mölders 2016). Moreover, regarding the FDI effect, in addition to the direct impacts of FDI, such as the competition effect and the linkage effect, technology transfer yields various indirect effects of FDI inflows, such as the acquisition of knowledge and technology, and labour mobility (Gui-Diby and Renard 2015). Thus, in addition to the two NIS processes, knowledge production and application, which generally have been used in previous studies, we propose introducing an additional construct of knowledge absorption for the other inputs of knowledge application, as shown in Fig. 1.

4. Research method

This study utilises several methods to answer the research questions. First, we implement relational network DEA to examine the efficiency of NIS in developing countries. Using the results of DEA, clustering analysis is carried out to discover certain typologies of countries according to their characteristics of innovation performance. Furthermore, classification by income aims to provide further implications for countries to find the closest targets to the benchmark. Figure 2 shows the aforementioned research method process. The subsections hereafter describe each method and the data in greater detail.

4.1 Relational network DEA model

Two major approaches to evaluate efficiency are stochastic frontier analysis (SFA) and DEA. SFA uses econometric techniques, while DEA uses linear programming, to build the efficiency frontier. Although each possesses its own advantages and disadvantages, the flexibility of DEA from non-parametric characteristics makes DEA models more widely used than the parametric approach (such as SFA) both in practice and theory (Kou et al. 2016). According to Nasierowski and Arcelus (2003), DEA often has been employed to measure the efficiency of NIS. This method essentially aims to gauge the relative efficiency of a group of decision-making units (DMUs). It is also applicable to various levels, depending on the purpose of analysis. In this study, each country is the DMU of DEA. Since DEA is a non-parametric approach, it does not need an assumption about distribution. DEA can simultaneously use multi-inputs and multi-outputs (Cruz-Cázares et al. 2013). In addition, DEA is very flexible and allows distinct economic assumptions regarding return to scale (Samoilenko and Osei-Bryson 2013) and computational orientation. However, sampling variability, data quality, and the presence of outliers can affect the sensitivity of the results. These are the major limitations of DEA.

The performance of a DMU cannot always be explained in a single process. There may be many cases that consist of multi-processes to demonstrate a phenomenon. The traditional DEA model disregards internal structure and interconnecting activities in a single production process. This constitutes the traditional DEA's limitation (Lu et al. 2014). Numerous studies have argued that its component processes need to be studied so that the origin of inefficiencies can be precisely distinguished (Kao 2014). In the literature, series

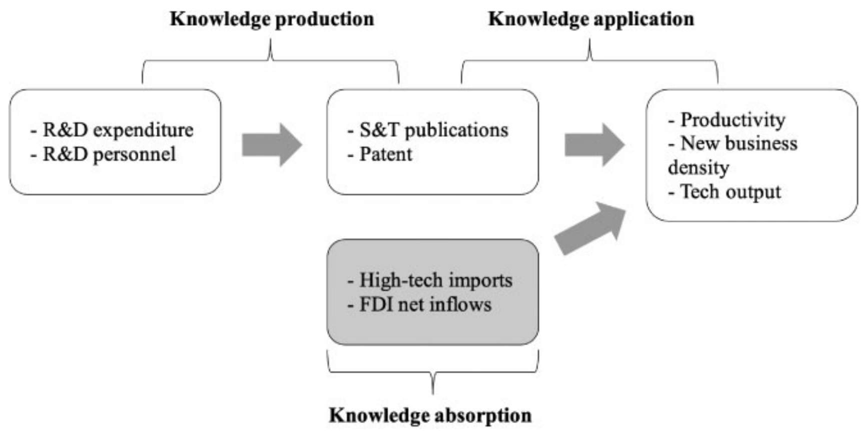

Figure 1. Process model for national innovation systems.

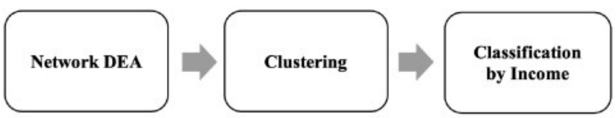

Figure 2. Flow chart of the research method.

structure and parallel structure, or a mixture of both, are the most basic structures to embody such multi-stage cases. They are called network DEA models (Färe and Grosskopf 2000). According to Kao (2014), a large number of studies have built on two-stage structures, and it can be largely divided into a basic two-stage structure and a general two-stage structure (for a comprehensive description of network DEA models, see e.g. Castelli et al. 2010; Färe and Grosskopf 2000; Kao 2014). The former refers to the network structure in which all inputs from outside are channelled into the first process to yield intermediate products, which are supplied to the second process to yield the final outputs. In the latter, the general two-stage structure, both stages are allowed to consume external inputs channelled from outside and to yield final outputs.

Considering the context of this study, the basic two-stage model seems inappropriate, as our model has the knowledge absorption process in the middle. Thus, we build the DEA model based upon the relational network DEA proposed by Kao (2009). By introducing dummy processes, this model enables the network system to be transformed into a series system with each stage of the series being a parallel structure. In our model, let each country's NIS be one DMU where KPP and KAP operate. The inputs of the system are X1, X2, X3, and X4, and the outputs are Y1, Y2, Y3, and Y4. Process 1 (KPP) uses X1 (R&D personnel) and X2 (R&D expenditure) to produce Z1 (patent) and Y1 (S&T publications). While Y1 goes for the output of the system, Z1 is supplied to the input of process 2 (KAP). Process 2 uses this Z1 together with X3 (high-tech imports) and X4 (FDI inflows) to produce Y2 (productivity), Y3 (new business density), and Y4 (technological output). Figure 3 presents the structure of the network DEA model of this study.

If we let v_i denote the multiplier associated with input i, where i = 1, 2, 3, 4, u_r the multiplier associated with output r, where r = 1, 2, 3, 4, and w_g the multiplier associated with intermediate product g, where g = 1, then, when calculating the system efficiency of DMU_k, each process must comply with the frontier condition in that the aggregated output must be less than the aggregated input, which is the additional condition to the conventional constraints for the system.

$$E_k = max\ u_1 Y_{1k} + u_2 Y_{2k} + u_3 Y_{3k} + u_4 Y_{4k} \tag{1.0}$$

$$\text{s.t.}\ v_1 X_{1k} + v_2 X_{2k} + v_3 X_{3k} + v_4 X_{4k} = 1 \tag{1.1}$$

$$\begin{aligned}&(u_1 Y_{1j} + u_2 Y_{2j} + u_3 Y_{3k} + u_4 Y_{4k})\\ &- (v_1 X_{1j} + v_2 X_{2j} + v_3 X_{3k} + v_4 X_{4k}) \le 0,\ j = 1, \ldots, n\end{aligned} \tag{1.2}$$

$$(u_1 Y_{1j} + w_1 Z_{1j}) - (v_1 X_{1j} + v_2 X_{2j}) \le 0,\ j = 1, \ldots, n \tag{1.3}$$

$$(u_2 Y_{2j} + u_3 Y_{3j} + u_4 Y_{4k}) - (v_3 X_{3j} + v_4 X_{4j} + w_1 Z_{1j}) \le 0,\ j = 1, \ldots, n \tag{1.4}$$

$$u_1, u_2, u_3, u_4,\ v_1, v_2, v_3, v_4, w_1 \le \varepsilon$$

Constraint (1.2) conforms to the system, and constraints (1.3) and (1.4) conform to the two sub-processes of the system, respectively. The additional constraints from the processes induce the relational network DEA model to be stricter than the traditional DEA model. Once the optimal multipliers v_i, u_r, and w_g are calculated from the models above, the efficiencies of the two processes are obtained as:

$$E_k^{(1)} = (u_1 Y_{1j} + w_1 Z_{1j}) / (v_1 X_{1j} + v_2 X_{2j}) \tag{2a}$$

$$E_k^{(2)} = (u_2 Y_{2j} + u_3 Y_{3j} + u_4 Y_{4k}) / (v_3 X_{3j} + v_4 X_{4j} + w_1 Z_{1j}) \tag{2b}$$

Thus, $E_k^{(1)}$ is to calculate the efficiency of KPP, and $E_k^{(2)}$, for KAP.

4.2 K-means clustering

In the previous section, we obtain the efficiency of the system and the process efficiency of KPP and KAP. Utilising the results obtained from (2a) and (2b), we implement clustering analysis to discover several typologies of countries in terms of knowledge production and application process efficiency. This method is a universal data-mining technique that uses the information contained in data that explains the objects. It partitions objects into mutually exclusive clusters, so that objects in the cluster are similar to each other and dissimilar to objects in other clusters (Samoilenko and Osei-Bryson 2008). The first goal of clustering analysis is to classify data sets into appropriate groups, and the second is to examine the differences between the characteristics of each group. Thus, clustering of countries

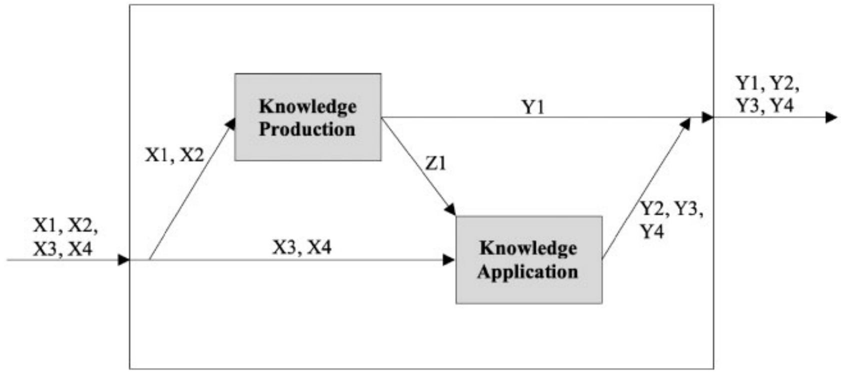

Figure 3. Structure of the network DEA in this study.

Table 1. Variables of the relational DEA model.

Type	Variable	Name	Description
Input for KPP	X1	R&D personnel	Researchers in R&D per million population, full-time equivalence
	X2	R&D expenditure	Total national expenditure on R&D as a percentage of Gross Domestic Product (GDP)
Input for KAP	X3	High-tech imports	High-technology imports minus re-imports (percentage of total trade)
	X4	FDI inflows	New investment inflows less disinvestment from foreign investors, divided by GDP
Intermediate products connecting KPP and KAP	Z1	Patent	Number of resident patent applications filed at a given national or regional patent office (per billion Purchasing Power Partiy (PPP)$ GDP)
Output from KPP	Y1	S&T publications	Number of scientific and technical journal articles (per billion PPP$ GDP)
Output from KAP	Y2	Productivity	Growth of GDP per person engaged (output per unit of labour input)
	Y3	New business density	Number of new firms: firms registered in the current year of reporting, per 1,000 population aged 15–64 years
	Y4	Technological output	High-tech and medium-high-tech output as a percentage of total manufacturers' output

seems useful for understanding them in greater depth from a certain perspective.

Clustering analysis has several algorithms, and K-means, which derives from the within-cluster variation measure, considered one of the most widely used methods (Jain 2010). The first step is to select a number (*K*) of cluster centres, called centroids. Next, objects are appointed to the nearest centroid based on the squared distance to the centroid (i.e. Euclidean distance). Then, the new centroid of each cluster is calculated on the basis of the mean of its appointed objects, and, equivalently, objects keep being reappointed to the closest cluster up to the minimisation of the within-cluster variations obtained so that no centroid changes.

One of the disadvantages of this method is that the number of clusters has to be specified in advance (Dai and Kuosmanen 2014). In other words, it requires prior information on the number of clusters prior to conducting the analysis. To address this issue, we first implement hierarchical clustering in order to identify the most appropriate number of clusters. Referring to the information obtained from the hierarchical clustering results, we assign the number of clusters, and K-means clustering analysis is performed as described above.

4.3 Data

The variables used in the DEA analysis are sourced from the Global Innovation Index, initiated and developed by the INSEAD Business School, Cornell University, and the World Intellectual Property Organization in 2007. Focusing on developing countries, we classify them based on income. Although there is no agreed-upon criterion by which to classify countries into developing and developed ones, a generally used method is gross national income (GNI) per capita. Accordingly, we assign high-income countries as developed countries and others as developing countries.

Table 1 provides the variables used for analysis in each stage, and the selection of variables relies on extant research (e.g. Carayannis et al. 2016; Guan and Chen 2012; Kou et al. 2016; Liu et al. 2015; Lu et al. 2014). As described in the previous section, there are three types of variables, including input, intermediate products, and output. Consistent with the relevant literature, the most commonly used inputs for KPP are R&D personnel and R&D expenditure, and S&T publications and patent for KPP output (e.g. Carayannis et al. 2016; Guan and Chen 2012; Lu et al. 2014). Regarding the outputs, S&T publications are the intermediate output of KPP, which is not used as the input for KAP. Moreover, patent is the intermediate product connecting KPP and KAP: it is the output of KPP and used for the input in KAP at the same time (e.g. Guan and Chen 2012; Kou et al. 2016). New inputs for KAP are high-tech imports and FDI inflows, which represent knowledge absorption. In addition to productivity and technological output, which are among the indicators frequently used in the relevant literature (e.g. Liu et al. 2015; Lu et al. 2014), we include new business density and technological output. It has been taken for granted that entrepreneurship is crucial for economic development (Naudé 2009) as an engine of economic growth through innovation, employment, and the welfare effect (Acs et al. 2008). Thus, new business density seems to be a meaningful measure to infer how well knowledge is

Table 2. Descriptive statistics.

Variable	Mean	SD	Min	Max
R&D personnel	1,119.991	825.332	109	3,194.8
R&D expenditure	0.459	0.354	0.0	1.2
S&T publications	10.106	6.691	0.6	28.5
Patent	2.234	2.507	0.1	8.9
High-tech imports	8.719	4.837	3.6	23.4
FDI inflows	3.734	2.523	0.6	11.5
Productivity	1.828	1.830	−2.0	7.8
New business density	2.003	1.993	0.0	8.9
Technological output	20.634	12.320	0.9	43.7

created and acquired to lead entrepreneurial activities. Particularly in the context of developing countries, the creation of new firms and businesses has further implications.

5. Results

5.1 Network DEA results

In this study, we used GNI per capita, which is generally used by international organisations, such as the International Monetary Fund, as the guideline to classify developing countries. Filtering out countries and excluding all missing data, thirty-two countries were analysed to calculate the efficiency. Table 2 presents the descriptive statistics of the variables used in the analysis. Although no generally accepted time lag was found in the relevant literature and 2- or 3-year time lags generally were used (Kontolaimou et al. 2016), we applied a 1-year time lag for each stage for 2014, 2015, and 2016, respectively, due to the availability of data.

The results of the efficiency analysis are presented in Table 3. Applying the data into the network DEA model, we obtained the system efficiency score of the entire system and the two sub-process efficiency scores of the thirty-two countries. System efficiency scores that consider only four inputs and four outputs of the system present the highest mean value. Among all, twenty countries obtained more than 0.8 scores. Armenia and Madagascar turned out to be efficient, while Costa Rica scored 0.219, which is the lowest. Looking at the sub-process, the third and fourth columns show the performance of KPP and KAP, respectively. Given that DEA yields relative efficiency within the target group of DMUs, this result implies that the performance gap of KPP is more widely dispersed than that of KAP among countries. For KPP, the results of only three countries—Armenia, Kyrgyzstan, and Madagascar—are efficient DMUs, while those of nine countries show efficient DMUs in KAP. An interesting point is that most countries' system efficiency tends to go hand in hand with the efficiency of KAP, except the outstanding example of Armenia. In contrast, many cases exist in which the efficiency score of KPP largely differs from the ones of system and KAP efficiency.

In KPP, Azerbaijan has the lowest score (0.080), followed by Indonesia (0.157), Algeria (0.216), Costa Rica (0.219), and Malaysia (0.288), which obtained scores of less than 0.3. Among them, Algeria, Azerbaijan, and Indonesia seem to be interesting cases that present relatively high KAP performance, indicating that Algeria and Indonesia are an efficient unit and Azerbaijan has a score of 0.873. A similar phenomenon is found for several other cases, such as the wide gap in KPP and KAP scores for countries, such as Russia, Tunisia, and Bulgaria.

Regarding KAP, only four countries, Costa Rica (0.162), Armenia (0.366), Malaysia (0.407), and Colombia (0.446), obtained scores of

Table 3. Efficiency results by country.

DMU	System efficiency	KPP efficiency	KAP efficiency
Albania	0.822	0.356	0.825
Algeria	0.997	0.216	1
Armenia	1	1	0.366
Azerbaijan	0.862	0.080	0.873
Belarus	0.993	0.977	1
Bosnia and Herzegovina	0.580	0.580	0.517
Brazil	0.735	0.427	0.740
Bulgaria	0.987	0.404	1
Colombia	0.519	0.519	0.446
Costa Rica	0.219	0.219	0.162
Egypt	0.711	0.355	0.716
Georgia	0.991	0.501	1
Indonesia	0.999	0.157	1
Jordan	0.863	0.349	0.874
Kazakhstan	0.763	0.391	0.766
Kenya	0.948	0.938	0.948
Kyrgyzstan	0.744	1	0.743
Madagascar	1	1	0.883
Malaysia	0.404	0.288	0.407
Mexico	0.601	0.500	0.618
Moldova	0.704	0.687	0.704
Pakistan	0.999	0.832	1
Peru	0.480	0.301	0.549
Romania	0.996	0.729	1
Russia	0.854	0.312	0.871
South Africa	0.998	0.847	1
Sri Lanka	0.999	0.562	1
Thailand	0.672	0.540	0.708
Macedonia, the FYR	0.879	0.677	0.881
Tunisia	0.876	0.361	0.895
Turkey	0.824	0.469	0.832
Ukraine	0.868	0.608	0.873
Mean	0.809	0.537	0.788

Table 4. Efficiency results by region.

Region	Number of cases	Mean		
		System	KPP	KAP
East Asia and Pacific	3	0.692	0.328	0.705
Europe and Central Asia	15	0.858	0.585	0.817
Latin America and Caribbean	5	0.511	0.393	0.503
Middle East and North Africa	6	0.862	0.321	0.871
South Asia	2	0.999	0.697	1.000
Sub-Saharan Africa	3	0.982	0.928	0.944

less than 0.5. Moreover, three other countries, including Bosnia and Herzegovina (0.517), Peru (0.549), and Mexico (0.618), presented KAP scores of less than 0.7. The rest had scores higher than 0.7. Among countries that had KAP scores above 0.7, only two countries, Kyrgyzstan and Madagascar, had higher KPP scores than KAP scores.

Table 4 shows the distribution of efficiency scores by region. The area consists of six regions, based on the regional classification criteria of the World Bank. It is worth noting that Sub-Saharan Africa has the highest or second highest average scores in all three types of efficiency results. Meanwhile, Latin America and Caribbean seems to fall behind other country groups in all three efficiency scores. They have the lowest average in both system and KAP efficiency, while being in third place in KPP scores.

Table 5. Clustering results.

Cluster	Member countries
A ($n = 7$)	Belarus, Kenya, Kyrgyzstan, Madagascar, Pakistan, Romania, South Africa
B ($n = 11$)	Albania, Brazil, Bulgaria, Georgia, Sri Lanka, Macedonia, Tunisia, Turkey, Ukraine
C ($n = 8$)	Bosnia and Herzegovina, Colombia, Egypt, Malaysia, Mexico, Moldova, Peru, Thailand
D ($n = 4$)	Algeria, Azerbaijan, Indonesia, Russia
Exception 1	Armenia
Exception 2	Costa Rica

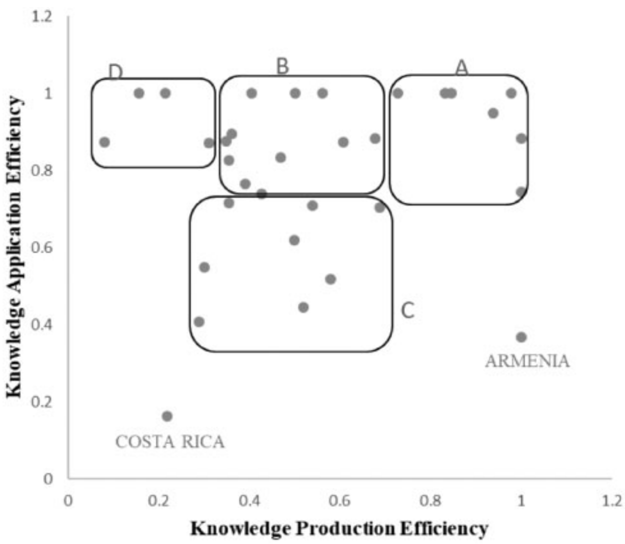

Figure 4. Clusters by the efficiencies of KPP and KAP.

5.2 Clustering analysis results

Table 5 presents the results of clustering analysis. We used each country's KPP and KAP efficiency score results as the input variables and implemented K-means clustering as described in Section 4.2. As shown in Table 5 below, four clusters were identified with two exceptional cases, Armenia and Costa Rica, which failed to find other member countries.

Cluster B accounts for the largest portion, with eleven member countries, followed by Clusters C, A, and D with eight, seven, and four member countries, respectively. The two axes of Fig. 4 show the efficiency of knowledge production and application, which are the criteria for the clustering analysis.

Cluster A seems to be relatively well-balanced and performs well both in KPP and KAP compared to other clusters. Clusters B and C exhibit a similar level of average scores in KPP, whereas their difference is found in the average scores of KAP: while Cluster C presents a similar degree of average scores in all three efficiency results, Cluster B exhibits an imbalance between KPP and KAP. Cluster D shows similar characteristics to Cluster B. It marked the lowest in the average of KPP scores, whereas it is the highest and the second highest one in KAP and overall system efficiency, respectively. Table 6 presents the basic descriptive statistics for such a comparison between clusters.

In KPP, Cluster A has the highest mean value of efficiency score, 0.903, by a large margin. The other clusters largely fall behind,

Table 6. Descriptive statistics of four clusters.

Cluster	KPP			KAP			System		
	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
A	0.903	1.000	0.729	0.939	1.000	0.743	0.954	1.000	0.744
B	0.464	0.677	0.349	0.881	1.000	0.740	0.873	0.999	0.735
C	0.471	0.687	0.288	0.583	0.716	0.407	0.584	0.711	0.404
D	0.191	0.312	0.080	0.936	1.000	0.871	0.928	0.999	0.854

marked below average 0.5. However, the situation is not the same for KAP. Cluster D, which when placed at the bottom of KPP by a large margin, took second place in KAP by a very small margin, followed by Clusters B and C. System efficiency seems to be similar to the situation of KAP regarding the descriptive statistics.

5.3 Classification by income

In addition, we further analysed the clustering results from the economic perspective, as presented in Table 7. Although we did not indicate it in Table 7, Armenia belongs to the lower-middle group and Costa Rica, the upper-middle II.

We sourced income data from the World Bank's database of GNI per capita (Atlas method) as of the year 2016. First, we divided the data based on the World Bank's criteria to classify countries into low-, lower-middle, and upper-middle-income groups. Then, we further divided upper-middle-income countries into two groups in order to specify more comparable countries from the perspective of economic availability. In general, most of the clusters' member countries are distributed across the various income groups, except the low-income group where only one country, Madagascar, is found.

6. Discussion

6.1 Major findings from NIS efficiency analysis

This study assessed the NIS efficiency of developing countries by decomposing innovation efficiency into KAP and KPP. Based on the relational network DEA perspective, the system efficiency that encompasses both KPP and KAP presented most of the countries to be relatively well-performing as shown in the average efficiency. Breaking down into KPP and KAP, the efficiency of each country's KAP tends to go hand in hand with the system efficiency overall. However, we found a wider gap among countries with respect to KPP than with respect to KAP. Thus, the most common cases are the group of countries that have a relatively high level of system and KAP efficiency, with a moderate level of KPP efficiency scores. Bulgaria, Georgia, and Turkey are the examples.

Moreover, countries who achieved good results even in KPP efficiency are the ideal cases among countries analysed; Belarus and Kenya are the examples. Although these two countries display similar results, the context behind it seems quite different if examining each of the variables used in the analysis. The most outstanding point in Belarus is the patent, which is the highest among countries, with four times more than the average. In addition, despite the low level of FDI and high-tech imports, the high performance of technological output might have resulted in excellent achievement in all three types of efficiency scores. On the other hand, Kenya did well in S&T publications and productivity growth as compared to its low input, such as the number of researchers FDI inflow. Kenya's

Table 7. Classification of countries by income.

	Cluster A	Cluster B	Cluster C	Cluster D
Low income (–1,025$)	Madagascar	–	–	
Lower-middle (1,026–4,035$)	Kenya Kyrgyzstan Pakistan	Georgia Jordan Sri Lanka Tunisia Ukraine	Egypt Moldova	Indonesia
Upper-middle I (4,036–8,000$)	Belarus South Africa	Albania Bulgaria Macedonia	Bosnia and Herzegovina Colombia Peru Thailand	Algeria Azerbaijan
Upper-middle II (8,001–12,475$)	Romania	Brazil Kazakhstan Turkey	Malaysia Mexico	Russia
Average	3,574	5,756	5,920	5,562

case may provide many lessons in terms of how to manage deficient resources in the most efficient way.

In contrast, exceptional cases are Armenia and Costa Rica. While the majority of countries tend to suffer more from KPP than from KAP, Armenia shows an efficient KPP score as opposed to the second lowest KAP efficiency (0.366) among all countries analysed. Armenia is notable in terms of its performance in S&T publications, which is the output both for the system and for its sub-component process, KPP, at the same time. We assume that it played the key role in obtaining the substantial results in the system and KPP efficiency. However, its technological output is one-quarter of the average of all DMU countries, and this may be one reason for its weak achievement in KAP efficiency. Given that KPP is being operated efficiently, Armenia seems to have much potential to improve KAP if it allocates more effort into efficiently and effectively utilising its knowledge base to be reflected in the application process.

Costa Rica is the other exceptional case, which, unfortunately, turned out to fall behind by a large margin in all three efficiency results. The notable point is its weak performance in the patent, which is in the eighth place from the bottom, as compared to the relatively high level in the number of R&D personnel. Furthermore, its second highest and fourth highest high-tech imports and FDI inflows, respectively, did not yield comparable results in all three output factors. Particularly, productivity growth was at the fifth position from the bottom. Taking these circumstances together, Costa Rica may be assumed to lack its own indigenous innovation activities. This situation may require a major overhaul of the NIS to create an appropriate ecosystem: abundant knowledge inflows from the outside should yield comparable achievement in knowledge application, while accompanied by great effort in generating an environment to produce indigenous knowledge and technology.

6.2 Three groups of NIS

To examine the efficiency results in a simplified manner, we clustered countries based on the efficiency results of KPP and KAP. We identified the following three groups: innovation leaders (Cluster A), knowledge application leaders (Clusters B and D), and innovation followers (Cluster C).

Innovation leaders mostly seem to consist of role models for other countries because they show high efficiency evenly in KPP and KAP. They are particularly outstanding in terms of KPP efficiency since it surpasses other groups by a large margin. As shown in Table 8, most countries in this group have a small number of R&D personnel, which is below the average of all DMU countries (1,119.0). However, outputs of KPP seem comparable to other cluster groups. Thus, countries in this group may keep up with current NIS operations, while paying attention to how to maintain efficiency as they expand the investment and the scale of innovation.

Table 8. Average value of variables by cluster.

Variable	Cluster A	Cluster B	Cluster C	Cluster D
R&D personnel	731.44	1,447.35	865.09	1,118.63
R&D expenditure	0.51	0.54	0.36	0.38
S&T publications	9.86	12.48	8.21	3.93
Patent	2.83	2.45	1.18	2.43
High-tech imports	7.53	6.72	12.39	6.68
FDI inflows	3.93	4.15	3.30	2.48
Productivity	1.41	1.85	1.73	2.90
New business density	2.19	2.64	1.39	1.53
Technological output	18.96	20.06	24.28	24.18

Knowledge application leaders possess the characteristics of a large imbalance between the efficiency of KPP and KAP. Such leaders show the highest average efficiency in KAP, but KPP falls significantly short of KAP. The large gap in KPP is particularly problematic for Cluster D, which shows the average efficiency of KPP at 0.191, while Cluster B, which is the other group in knowledge application leaders, is 0.471 on average. The most outstanding part is the lowest level of S&T publications (3.93 on average). This number is half of the average of Cluster C, which has almost 30 per cent less R&D personnel. In contrast, Cluster D's technological output is second highest, slightly behind Cluster C.

An interesting point is that knowledge application leaders account for almost half of the total cases. This tendency differs from that found in relevant literature that has studied developed countries (e.g. Carayannis et al. 2016; Guan and Chen 2012). It can be assumed that, in many cases, developing countries have relatively weak knowledge bases and are not sufficiently equipped with an institutional setting to promote innovation. Another possibility is that there is too much dependence on foreign technology or investment. In this case, there seems a need for more incentives and policy instruments for knowledge creation, such as intellectual rights protection (Guan and Chen 2012). If inputs are already sufficiently large, more consideration and efforts towards appropriate R&D management and financing are requisite rather than simply increasing investment in inputs. Issues related to sound resource allocation and innovation mechanisms for such resources to be fully exploited should be addressed. If so, the improved efficiency of KPP would yield improved KPP output, which would be automatically related to the increased KAP output, since this group is already efficient in the level of KAP. Furthermore, this group's high efficiency in KAP enables it to expect the reversed flow of knowledge and skills. Given that the industry sector seems to perform well, active collaboration between industry and academia would provide opportunities for improved KPP.

Innovation followers mostly consist of the most lagging countries in both KPP and KAP. For KPP, given the equivalent efficiency for KPP to the knowledge application leaders' group, similar remedies should be provided. Unlike knowledge application leaders, additional problems appear with regard to the significant inefficiency of KAP compared to others. The interesting point is that their high-tech imports are almost twice that of other clusters, and the average of technological output is the highest, leaving new business creation lowest. In this case, more attention to the absorptive capacity or technological learning mechanism seems necessary to overcome inefficiency and to ensure their own technological capability rather than yielding outcome via technological dependence. In addition, government incentives for entrepreneurial activity and appropriate financing and funding for business creation would be beneficial.

6.3 Implications from the economic perspective

We further classified member countries of each cluster by income so that countries could find closer targets to the benchmark from the perspective of economic resources. For example, Romania may be a more feasible benchmark for countries, such as Turkey and Russia, as they have similar economic levels, assuming equivalently available resources. In addition, Kenya can be a reference to countries, such as Tunisia and Egypt. Table 9 presents the average value of NIS efficiencies by income group.

Available resources and budget are more critical for developing countries, which generally suffer from a lack of resources. Meanwhile, the highest average income of innovation followers is worth noting. This is a similar issue across countries in the upper-middle income II bracket, which shows the lowest average in all three efficiencies on average. A common characteristic is that the majority of countries show a high level of high-tech imports and technological outputs as compared to others, and this could be partially attributable to their economic advancement. Although their economies are on the cusp of entering the high-income group, questions remain about the sustainability or structural limitations of these economies owing to such issues as technological dependence. For example, Zeng and Fang (2014) asserted that China might fall into a middle-income trap if it maintained its over-dependence on foreign technology and investment, and recommended China to be selective about FDI and to accumulate more capability for indigenous innovation.

In fact, this is not only the case for this group. Overall, the majority of countries analysed suffer from relatively low efficiency in KPP. It is undeniable that knowledge absorption from developed countries in order to acquire advanced knowledge and technology is critical to development under the current environment, where technological advancement mainly relies on foreign knowledge and technologies rather than domestic (Keller 2004). It enables to not only rapidly catch up, but also leapfrog the routes of development. However, this seems not to always be an effective way. Even though knowledge and technology are transferred via channels, such as trade and FDI, a certain level of capacity is required to properly absorb and apply them in various other ways (Fu et al. 2011). Thus, in order to achieve sustainable development, more attention is required to accumulate a country's own innovation capability, such as absorptive capacity or enhanced technological learning mechanism.

Table 9. Average value of NIS efficiencies by income group.

Income group	# of countries	System	KPP	KAP
Lower-middle	12	0.892	0.613	0.843
Upper-middle I	11	0.799	0.500	0.800
Upper-middle II	8	0.675	0.417	0.675

7. Conclusion

7.1 Theoretical contributions

As the role of innovation in economic growth increases, various parties have paid attention on how to manage innovation to achieve optimal performance. At the country level, NIS has been popular to view national innovation from a systemic approach, and some scholars have attempted to assess the efficiency of innovation systems. This study followed this line and made several theoretical contributions to the literature. First, this study contributes to the literature of measuring innovation efficiency at the country level. Considering the importance of innovation management across various levels of entity, such stream of research is worthy of additional attention in academia, as well as in the real world. Moreover, developing countries constituted the object of our analysis. In the literature, there has been little research on the efficiency of innovation at the national level, and, to the best of our knowledge, most of this research has examined developed countries. Given that innovation is not an issue only related to developed countries, the attention to developing countries may contribute to the relevant literature, both academically and practically. In fact, the current international economy calls for a deeper understanding of developing countries, as their role in the global economy is growing.

Furthermore, following the extant literature that has examined the efficiency of NIS in the context of two-stage analysis, we incorporated two additional intermediate inputs in KAP to capture the knowledge absorption activity. This is an effort to take the context of developing countries into account, whose knowledge base is relatively weak, and knowledge acquisition from external sources is crucial. We expect that two-stage-based analysis will allow examining the internal operations of innovation investment and effort, while the introduction of knowledge absorption activities better describes the performance of NIS in a developing countries context. In this sense, the application of the relational network analysis may reinforce such purpose by demonstrating the interactive relationship between the two sub-processes, and facilitating clarification of the embedded inefficiency.

7.2 Practical contributions

The practical contributions of our research are as follows. Given the importance of developing countries, the assessment of NIS efficiency provides a general understanding of innovation status. It might be beneficial to elucidate the overall operation of innovation systems and to capture potential business opportunities. Currently, while the economies of developed countries stagnate, those of developing countries are driving global growth, leading to the expansion of the middle class. The growth of the middle class implies enlarged consumption and needs, thereby leading to opportunities for innovation. Moreover, the population at the so-called 'bottom of the pyramid' is a force that cannot be overlooked in innovation opportunities, as several cases have proven. In this sense, the focus of this study on developing countries seems to provide meaningful insight into the world. Moreover, the results may enable policymakers to determine the relative position of a country and to provide appropriate policy directions. A process-oriented approach to NIS and efficiency at each stage could offer better clues to improve the status. More fundamentally, our study may be referred to as an evaluation tool, so that each government can assess its status and create an effective strategy.

In addition, we implemented a clustering analysis to classify countries into several groups with similar characteristics based on the results of an efficiency analysis. It identified several groups based on NIS operations, such as innovation leaders and followers, so that each group could be given precise policy suggestions. For example, the vast majority of countries are found in the application leaders group, which shows the imbalance between KPP and KAP efficiency, mostly suffering from KPP operations. This reveals the problem of developing countries, whose knowledge base is relatively weak and calls for a particular solution. Finally, we attempted to specify each group based on an economic level and to suggest more feasible targets for benchmarking in each case. It is important to note that developing countries often suffer more from a lack of resources than do developed countries, and economic status among developing countries is considerably heterogeneous. Consideration of economic level seems necessary to identify realistic benchmarks with equivalent resources available.

These aforementioned policy implications are applicable not only to each government, but also to international organisations who seek efficient and effective allocation of resources. Innovation is one of the key pillars composing the Sustainable Development Goals proposed by the United Nations. As such, there are increasing efforts for STI as a part of international development and aid (e.g. the Commission on Science and Technology for Development (CSTD), which is a subsidiary body of the United Nations' Economic and Social Council). In this sense, our study suggests an approach from the STI perspective, beyond the traditional method of country classification, such as region and income. Such way of understanding may be more effective as they build up development and/or aid plans relevant to STI, so that optimal allocation of resources is made.

7.3 Limitations and future research

The limitations of this study are mostly concerned with data. In matching all data to our input and output variables, a large number of countries were omitted. Our analysis would have been enriched if more countries had been assessed. In particular, the analysis would have benefited from securing data on low-income countries. In our model, the only low-income country that was retained in the sample was Madagascar, but more samples in this income group are necessary to understand the innovation performance of these countries. We anticipate that future studies will overcome this problem as more data accumulate and time passes. In this case, time-series analysis would be viable so as to reveal a country's NIS movements. Other directions for further study include identification of the causes of differences among developing countries and a case study on best practices.

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