Effectiveness of knowledge economy determinants: Comparative study among Moderate Innovators

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Abstract

Nowadays, innovations play an important role in the globalized competitive environment and each economic actor is pushed to find new sources of competitive advantage and to innovate own products or services. Therefore, the European Commission annually publishes own Innovation Union Scoreboard, which provides a comparative assessment of the EU member states' research and innovation and ranks countries according to their innovation performance. Each country is divided into one of four groups according to its innovation performance: innovation leaders, strong innovators, moderate innovators, and modest innovators. However, in the knowledge economy era, countries are facing new challenges in dealing with new determinants of firms´ performance (and also the prosperity of society in regions). These determinants (of knowledge economy) affect innovation activities at local, regional, national and also supra-national level. In this study, we offer new way of how to measure the effectiveness of knowledge economy determinants application by using Data Envelopment Analysis within European countries – specifically within moderate innovators with innovation performance below the EU average. Moderate innovators realize many various types of policies – a policy mix of business RandD and innovation-focused policy coupled with support for competitive RandD. However, the application of different approaches is variously effective and also in this one "moderators" group the leaders and the catch-up countries are appearing. The causes of differences in success should be analyzed.
Moreover, we compare the ranks of moderate innovators according to their innovation performance measured by the European Commission with our results and provide some practical implications on how to become more efficient in the use of knowledge economy determinants.

Key words: knowledge economy, comparative study, innovation, moderate innovator

JEL Classification: R38, R50, R58

1 Introduction

It has been many times postulated that the economic processes of many developed countries have changed over the last few decades. They have moved from a production-based economy to a knowledge-based one (Powell and Snellman, 2004). However, this means that many firms have to become knowledge-intensive and add knowledge to their production processes (Jenssen and Nybakk, 2013). Logically, these firms are becoming dependent on the ability to transform their employees' soft assets, technology and other inputs to innovation and economic value (Anand, Gardner and Morris, 2007).

In practice, this means that firms need to consider carefully their ability to acquire unique asset whose ownership and use will mean a competitive advantage gaining. There are some typical examples: the ownership of unique production factors, patents or utility models, as well as unique technologies. This requires the considerable financial resources (private investments), but also the ability to enter into strategic partnerships (alliances), establish cooperative relationships and take advantage from the proximity of scientific research potential (Chen and Hua Tan, 2013). However, every company may not have all the components of the knowledge potential to be a knowledge-intensive firm. Many scholars agree that the recruitment, development, and retention of highly talented people are crucial to the effective development of an economic unit operating in an international context (Schniederjans, Schniederjans and Schniederjans, 2015). However, they emphasize that every country is otherwise matured in the field of innovation, and draws attention to the need to diversify approaches to innovation supporting in "different levels of innovative development" countries (Esparcia, 2014; Prokop, Stejskal and Kuvikova, 2017).

The whole topic should also be examined from a macroeconomic point of view. The functioning and prosperous firms, that provide high quality work to skilled workers, contribute significantly to economic growth and social welfare (Leigh and Blakely, 2016). Also the politicians understood this importance and define the public policies, what should support the creation of a knowledge environment in their country or region (von Krogh and Geilinger, 2014). They sometimes also offer the financial schemes (public budget expenditures). But one question remains - the efficiency of all public policies, schemes, and support in this knowledge economy issues. Therefore, the aim of this paper is to propose a new way of measuring the effectiveness of selected determinants of knowledge economy.

The remainder of this paper is divided in the following way. The first section is focused on the problematic of the knowledge economy determinants. The second section describes the methodology and analysis results. The last section brings the conclusions and some political implications and recommendations.

2 Theoretical background

It has already been emphasized above that knowledge-based activities (implemented in firms and other organizations) are the substance of the knowledge economy. Many scholars have focused on the creation and accumulation of knowledge-based competencies in their studies in order to yield long-term survival (Mazloomi Khamseh and Jolly, 2008). However, these competencies must be perceived in a broad context; it covers abilities of labors, knowledge (innovation) absorption capacity and the quality of the knowledge environment (eco-system) (Del Giudice, Carayannis and Maggioni, 2016).

An interesting review is provided by Mazloomi Khamseh and Jolly (2008), who report in their paper about the key focuses of researchers on knowledge and cooperation networking. Firstly, knowledge is a source of competitive advantage, (2) knowledge creation as a reason for creating a cooperative chain/network, (3) knowledge absorption, (4) collaborative knowledge. From the studies mentioned above, there are different knowledge functions that require specific conditions and environmental elements for effective application. The mentioned “key focuses” logically correspond to the four basic pillars of the knowledge economy framework. The first is an economic incentive and institutional regime that provides efficient and efficient mobilization and allocation of resources and stimulates creativity and incentives for the effective creation, dissemination and use of existing knowledge. Second talks about educated and skilled workers who can continuously upgrade and adapt their skills to effectively create and use knowledge. The third pillar is an effective innovation system of firms, research centers, universities, consultants, and other organizations that can keep up with the knowledge revolution and tap into the growing stock of global knowledge and assimilate and adapt it to local needs. The last pillar is a modern and adequate information infrastructure that can facilitate effective communication, dissemination, and processing of information and knowledge (Chen and Dahlman, 2005; Van Winden, Van den Berg and Pol, 2007).

From these pillars, it is possible to derive partial determinants that influence the efficiency of the knowledge economy. Efficiency should be examined from the point of view of outputs and inputs. Typical outputs undoubtedly include innovation as the primary output of knowledge processes (Powell and Snellman, 2004). They are commercialized and bring economic benefits to an innovator or owner of knowledge. In this process, there is a contribution to GDP creation, strengthening national and regional growth and economic development. It should be remembered that it is not easy to measure these outputs, so many scholars perceive rather as patent variables or utility patterns as the output variable (Olssen and Peters, 2005).

Inputs to innovation or knowledge processes are different. As mentioned above, it is mainly HRST stock (human resources for science and technology). HRST are the crucial survival and growth factor for economies. The human resource competitiveness is the most important factor in achieving economic competitiveness (Chou, Sun and Yen, 2012). Scholars are led to analyze the real and potential inflows into HRST, which they believe are important for increasing efficiency and productivity (Chou, Hsu and Yen, 2008).

Another significant input in the innovation processes is the funds. We include here both types - private and public RandD expenditures. The real significance of this financial support is being discussed by experts´ discussions (David, Hall and Toole, 2000; Guellec and Van Pottelsberghe De La Potterie, 2003; Becker, 2015). It is undeniable, that without the RandD expenditures it is not possible to create an environment suitable for the development of the knowledge economy (especially hard infrastructure) and to support the broad involvement of economic entities in cooperative-based or knowledge-based networking (Johannissson, 1998; Hayter, 2013).

It turns out that it is necessary to carry out high-quality research that also identifies determinants in the individual countries (regions or industries) that will bring the greatest outcomes and effects.

3 Research Methodology and Data

In this paper, the parametric approach – Data Envelopment Analysis (DEA) – was used as a model specialized tool for assessing the effectiveness, performance and productivity of comparable production units (homogeneous units: decision making units - DMUs) based on the size of inputs and outputs. DEA uses mathematical programming models to estimate best-practice frontiers without a priori underlying functional form assumption through computing multi-input/multi-output values and calculates a maximal performance measure for each DMU relative to all DMUs in the countries (EU 28) under observation (Guan et al., 2006). The model can be built on the assumption of constant returns to scale (one unit of input generates one unit of output), when all DMUs are operating at optimal scale (CCR model). Rather unrealistic condition is solved by introducing variable returns to scale (VRS) considering all types of returns: increasing, constant or decreasing (BCC model).

The efficiency can be increased either by increasing outputs under increasing returns to scale, or by reduction in outputs under decreasing returns to scale (Hudec and Prochadzkova, 2013). DMUs convert multiple inputs into outputs, meaning that a set of units that produce the same or equivalent effects that are referred as the outputs of these units (Staničkova and Melecky, 2011). DEA has become the most prominent method for performance measurement and DEA models are derived from Farrell's model for measuring the effectiveness of units with one input and one output (Stejskal and Hajek, 2016).

The mathematical formulation of DEA models considers the existence of a set of homogeneous production units $U_1, U_2, \ldots, U_n$, wherein each of the units produces r outputs and subsequently using m inputs (Dlouhý et al., 2007). Then, $X = \{x_{ij}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n\}$ is considered as input matrix a $Y = \{yij, i = 1, 2, \ldots, r, j = 1, 2, \ldots, n\}$ is considered as output matrix. Efficiency rate of U_q unit is generally expressed as follows (Jablonský and Dlouhý, 2004):

$$\frac{weighted\ sum\ of\ inputs}{weighted\ sum\ of\ outputs} = \frac{\sum_i u_i y_{iq}}{\sum_j v_j x_{jq}}, \qquad (1)$$

where v_j, $j = 1, 2, \ldots, m$ are weights assigned to j-th input;
u_i, $i = 1, 2, \ldots, r$ are weights assigned to i-th output.

The scales in this model stand out as variables that are not known.

The principle of DEA models is that when evaluating the efficiency of a production unit U_q it maximizes its efficiency level, assuming that the efficiency rate of all other DMUs cannot be higher than 1 (100 %). The weights of all inputs and outputs must be greater than zero so that all the considered characteristics in the model are included (Dlouhý et al., 2007). Dlouhý et al. (2007) formulates this model as follows:

to maximize
$$\frac{\sum_i u_i y_{iq}}{\sum_j v_j x_{jq}} \qquad (2)$$

while
$$\frac{\sum_i u_i y_{iq}}{\sum_j v_j x_{jq}} \leq 1, k = 1,2, \ldots, n,$$

$$u_i \geq \varepsilon, \quad i = 1,2, \ldots, r$$
$$v_j \geq \varepsilon, \quad j = 1,2, \ldots, m$$

where ε is an infinitesimal constant that ensures that the calculated weights of inputs and outputs are greater than zero.

For our cross-country analyses within the EU 28 countries (with focus on Moderate Innovators), we used input-oriented VRS model operating with variable returns to scale and data from Eurostat databases (2017). Selected inputs and outputs are shown in Table 1. We chose 4 input variables (provided by Eurostat) that were grouped in the Science and Technology themes that could be expected as main determinants of the knowledge economy (David and Foray, 2002; Cooke and Leydesdorff, 2006) and one input variable represented by the Gross Domestic Product. We compare countries efficiency within the EU 28 and within groups of innovation performance (measured by the European Commission[1]). We clarify whether the economies of the EU 28 use effectively the selected determinants of the knowledge economy and identify the economies with low efficiency. For low-efficient economies, the DEA software proposes some inputs and outputs reductions that will help them to become more efficient. The optimal time delay between input and output variables

[1] Countries were grouped according to their innovation performance measured by European Commission in Innovation Union Scoreboard 2016.

was analysed by number of researchers (e.g. Mansfield, 1991; Hollanders and Celikel-Esser, 2007; Wang and Huang, 2007). Following previous studies (Guan and Chen, 2012; Hudec and Prochadzkova, 2013), we chose four years time delay – the years 2011-2015.

Table 1 Variables involved in the model

Input variables (2011)			Output variable (2015)	
Determinant	**Variable**	**Description**	**Variable**	**Description**
Inflows into HRST	First and second stage of tertiary education	Eurostat indicators on real and potential inflows into the stocks of HRST	Gross domestic product	Gross domestic product (GDP) and its growth represent one of the most frequently used indicators of economic growth (Grier and Tullock, 1989; Chen and Dahlman, 2005)
Stock of HRST	Persons employed in science and technology	Eurostat indicators on stocks of HRST		
RandD expenditures	Total intramural RandD expenditure (GERD)	Intramural RandD expenditures are all expenditures for RandD performed within a statistical unit or sector of the economy during a specific period, whatever the source of funds		
Innovation	Patents granted by the USPTO	Patent information is based on the priority year and is made available after the date of publication of the application. This statistical unit is the innovative activity within a country's borders that result in patent granted by the USPTO.		

Note: HRST = Human Resources in Science and Technology; First stage of tertiary education not leading directly to an advanced research qualification, Second stage of tertiary education leading to an advanced research qualification; GERD = Gross domestic expenditure on RandD; USPTO = United States Patent and Trademark Office
Source: own based on Eurostat databases

4 Results

Results of input-oriented VRS model are shown in Table 2. DMUs (countries of EU 28) that efficiently used selected determinants of knowledge economy reached the rate of effectiveness 1,000. Countries that did not reach the rate of effectiveness 1,000 were not considered effective (less rate of effectiveness means less efficiency of the country). Results show that 15 countries of the EU 28 (54 %) were effective.

Only Germany was considered effective within the group of innovation leaders (1 from 4; 25%). Ireland, United Kingdom, Luxembourg and France were considered effective within the group of strong innovators (4 from 7; 57%). Surprisingly, approximately 65% of moderate innovators were considered effective and 1 of 2 (50%) modest innovators (Romania) was also considered effective. We can see that countries below the EU 28 average of innovation performance more effectively used selected determinants – specifically moderate innovators. Number of moderate innovators realizes many various types of policies – a policy mix of business RandD and innovation-focused policy coupled with support for competitive RandD and are pushed (tent) to catch up with countries from the group of strong innovators.

The advantage of the DEA model is that it provides practical implications (for each country) on how to improve and how to change inputs and outputs to become (more) efficient. Input-oriented models propose changes focusing primarily on input variables (or even minor changes on the output side). Table 2 therefore shows both original values (obtained from the Eurostat databases) and adjusted values (provided by DEA) that show how the input (output) variables should be reduced/increased.

Table 2 Results of input-oriented VRS model

Innovation performance	Country	DEA efficiency	Input Variables (2011)								Output Variable (2015)	
			Inflows into HRST (in thousands)		**Stock of HRST** (in thousands)		**RandD expenditures** (in thousands Eur)		**Innovation** (no. of units)		**GDP** (in millions Eur)	
			Orig.	**Adjust.**	**Orig.**	**Adjust.**	**Orig.**	**Adjust.**	**Orig.**	**Adjust.**	**Orig.**	**Adjust.**
Innovation leaders	Sweden	0,80762	463,5	374,4	142,7	115,2	13157434	7647679,2	1481,5	970,4	447009,5	410351
	Denmark	0,81380	258,9	210,7	72,2	53,9	7299197	3749541,6	566,9	461,3	271786,1	3032820
	Finland	0,53178	308,3	152,8	55,1	29,3	7163692	2201859,5	756,9	256,4	209149	447009,5
	Germany	**1,00000**	2763,1	2763,1	1197,2	1197,2	75569073	75569073	9976,5	9976,5	3032820	20251,7
	Netherlands	0,77597	780,0	605,3	254,4	197,4	12235300	9494238,3	1530,5	1144,7	676531	339896
Strong innovators	Ireland	**1,00000**	196,3	196,3	36,6	36,6	2665900	2665900	316,8	316,8	255815,1	175697,4
	Belgium	0,80501	462,4	372,3	96,2	77,4	8171000	4766732,6	653,5	526,1	410351	45286,5
	United Kingdom	**1,00000**	2492,3	2492,3	895	895	31547068	31547068	3571,9	3571,9	2577280,1	2577280,1
	Luxembourg	**1,00000**	5,4	5,4	4,6	4,6	631400	631400	51,9	51,9	51216,2	109674,2
	Austria	0,76424	361,8	276,5	145,7	69,9	8276335	4347848,9	693,9	530,3	339896	429794,2
	France	**1,00000**	2259,4	2259,4	569,8	569,8	45111514	45111514	4536,1	4536,1	2181064	43846,9
	Slovenia	0,63744	107,1	68,3	14,8	9,4	894213	353551,4	32,6	20,7	38570	78685,6
Moderate innovators	Cyprus	**1,00000**	32,1	32,1	7,8	7,8	88883	88883	6,5	6,5	17637,2	24348,5
	Estonia	0,37852	69,1	26,2	19,3	7,3	384447	144679,9	30,3	11,5	20251,7	255815,1
	Malta	**1,00000**	11,5	11,5	6,8	6,8	46195	46195	5,3	5,3	9250,3	676531
	Czech Republic	0,72466	446,2	323,3	90,7	50,0	2551989	1849332,8	123,1	89,2	166964,1	271786,1
	Italy	**1,00000**	1967,6	1967,6	279,4	279,4	19810600	19810600	1843,1	1843,1	1642443,8	17637,2
	Portugal	**1,00000**	396,3	396,3	64,3	64,3	2566450	2566450	30,1	30,1	179539,9	159963,7
	Spain	**1,00000**	1950,5	1950,5	212,4	212,4	14184295	14184295	625,4	625,4	1075639	2181064
	Greece	**1,00000**	659,8	659,8	30,4	30,4	1391156	1391156	43,6	43,6	175697,4	1075639
	Hungary	0,67680	381,9	258,5	54,5	36,9	1204629	815290,5	112,6	69,4	109674,2	9250,3
	Slovakia	**1,00000**	226,3	226,3	36,7	36,7	468439	468439	19,5	19,5	78685,6	209149
	Poland	**1,00000**	2080,3	2080,3	234,2	234,2	2836165	2836165	155,3	155,3	429794,2	179539,9
	Latvia	0,86964	103,9	63,5	23,6	10,7	140730	122384,5	9,4	8,2	24348,5	37330,5
	Lithuania	**1,00000**	187,1	187,1	30,4	30,4	282698	282698	9,7	9,7	37330,5	51216,2
	Croatia	0,86349	154,0	132,9	15,4	13,3	336373	290453,6	18,2	15,7	43846,9	1642443,8
Modest innovators	Bulgaria	0,88211	285,3	212,8	31,2	20,5	219637	193743,8	17,3	15,2	45286,5	166964,1
	Romania	**1,00000**	871,8	871,8	65,6	65,6	657411	657411	47,6	47,6	159963,7	38570

Source: own

These results show that there is a need to focus on each selected variable (determinant of the knowledge economy) to avoid increasing inefficiency and to reduce the number of countries that are inefficient. In the last part, we therefore propose some practical implications for policy makers within EU 28 countries.

5 Conclusions

The effectiveness of the determinants of the knowledge based economy depends on pillars which support a successful knowledge economy. The pillars are determined by the institutional and economic regime that is favorable for the creation, dissemination, and utilization of knowledge. A skilled and well-educated population can create and use knowledge efficiently. A more educated population is inclined to be more technically sophisticated, producing higher demand for knowledge. The information infrastructure that facilitates the communication, dissemination, and processing of information and technology is also an effective determinant of the knowledge-based economy. In this study, we sought to propose a new way of measuring the effectiveness of the knowledge economy determinants using the Data Envelopment Analysis. The analysis focused on European countries, specifically moderate innovators with innovation performance below the EU average.

The results of the Data Envelopment Analysis have shown that out of the 28 countries of the EU, 15 countries that constitute about 54 % were effective. A country such as Germany was the only effective innovative performance among the list of innovative leaders. The results also show that among the strong innovators, Belgium, Austria and Slovenia were found to be inefficient. The moderate innovators class which was the focus of this paper had the highest number of efficient countries with only Estonia, Czech Republic, Hungary, Latvia and Croatia been the inefficient countries.

The results of the analysis therefore call for practical implications and suggestions on how ineffective countries within the EU can become more efficient in the use of knowledge economy determinants. First of all government policies can encourage innovation by persistently reforming and bringing up-to-date the institutional and regulatory framework within which innovative activity occurs (Hajek, Stejskal, Prochazka, 2016). In this regards, compulsory reforms is needed to make public policy more favorable to innovation in a range of policy areas (financial markets, education, general business environment, international trade and international investment and labour markets).

EU countries can in addition have fiscal incentives that can raise private RandD, especially when firms are financial constrained. Tax cuts for private RandD can provide a robust stimulus to business RandD than direct government support. EU 28 governments can equally play a more direct role in encouraging innovation. Public investment in basic science and technology research can play a significant role in developing ICT potential of EU countries. Countries where education is considered ineffective and inappropriate can invest a high percentage of its GDP to strengthen is human capital base. Lastly EU 28 countries need policy reforms that will strengthen the productivity outcomes and innovation. They can expand the business environment for innovation because businesses are the focal driver of innovation.

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