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EVALUATION OF THE EU COUNTRIES' INNOVATIVE POTENTIAL – MULTIVARIATE APPROACH

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ABSTRACT

The aim of the article is to work out a synthetic measure for estimating country's innovation potential (CIP) of EU economies. For the purpose of the research, data from the European Statistical Office (Eurostat) are used and several indicators are organized by four different areas of analysis, i.e. investment expenditure, education, labour market and effects. Applying multi-dimensional statistics allows us to reduce the primary set of diagnostics variables and, simultaneously, identify those which best describe the potential. The final step is linear ordering of EU countries according to their innovative potential on the basis of CIP synthetic measure. The rating is compared with other ratings based on the recognized *Summary Innovation Index* and *Global Innovation Index*. The main conclusion is that the methodology of innovativeness assessment remains an open issue and requires further research. The most important task is the selection of indicators, followed by statistical verification in relation to their importance to innovativeness. The results show that there is a tendency to between the author's ratings and other already published ratings of innovativeness.

Key words: innovativeness, Innovation Union Scoreboard, European Union, cluster analysis, factor analysis.

1. Introduction

Changes in knowledge resources as well as ability to utilize them determine the possession of country in the contemporary world. Capability of using knowledge and information as well as efficient application of modern technology form the basis of building up innovativeness (compare Soete (2000), OECD (2005), Pilat & Woelfl (2003)). Innovativeness represents capability of performing creative acts, inventing new ideas and inventions. Innovativeness manifests itself in an attempt to search for new combinations of production factors, introducing new value added to competitive products as well as

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application of knowledge achievements in the production process (Granstrand (1999)). Innovations are a significant factor of the competitiveness of the economy. They are an inherent part of constant and sustainable economic development. Moreover, their importance increases when the country's economy becomes more developed (Cornelius & McArthur (2002)). The question of innovativeness and innovation on micro, meso and macroeconomic level was reflected in the theory of economy and management as well as multiple articles, e.g. by P. Drucker (2004), J. Schumpeter (1960), M. Porter (2001), E. Rogers (2003), and others. Nevertheless, it is Joseph A. Schumpeter (1883 – 1950) who is believed to have coined the term 'innovation'. He described economic process as a creative act which means creating, designing and implementing innovation (Schumpeter (1960)). The authors of the article were encouraged to raise the topic by the lack of unanimity in terms of measuring innovative potential of economies. The purpose of the article is a statistical analysis of factors influencing innovativeness of EU economies. The result of the quantitative analyses is linear ordering of EU countries according to the level of their innovative potential. The rating was compared with the outcome presented in *Innovation Union Scoreboard* (*IUS*) based on *Summary Innovation Index* (*SII*).

2. Measuring innovativeness

Measuring innovation remains a relatively new branch of statistics, although it is gaining a wide interest from both practitioners as well as theorists. One of the best known studies on innovativeness is *Global Innovation Index – GII*[3]. It is an annual report released by experts of Johnson Cornell University, one of the largest management and business schools in the world – INSEAD – the Business School for the World and *The World Intellectual Property Organization – WIPO*). The framework is composed of 79 individual indicators describing innovation, which was divided into 7 categories, i.e. institutions, human capital and research, infrastructure, market sophistication, business sophistication, knowledge and technology output and creative output (Dutta, Lanvin & Wunsch-Vincent (2015)).

European Innovation Scoreboards presents another source of information on innovative activity in particular member states. EIS distinguishes the following products: *Innovation Union Scoreboard*, *Regional Innovation Scoreboard* and a new element with its pilot implementation in 2013 – *European Public Sector Innovation*[4]. Data used for creating *EIS* come from multiple primary resources but also public data obtained from European Patent Office and Office for Harmonization in the Internal Market. Individual indicators collected for *EIS*

[3] The Global Innovation Index, https://www.globalinnovationindex.org/content/page/GII-Home, access 22.10.2015.

[4] For more details see: European Commission portal, http://ec.europa.eu/growth/industry/innovation/facts-figures/scoreboards/index_en.htm, European Commission (2013).

allow for working out the *Innovation Union Scoreboard* based on a composite innovation indicator *Summary Innovation Index* (*SII*[5]). Currently, 25 indices divided into five categories are used to estimate SII. The first three sub-groups are input indicators whereas the next two – output ones. *Input* comprises: a) innovation enablers that illustrate conditions for innovation development, which are not directly related to the activity of enterprises, b) *firm's activities* – present innovative activity of a company. *Output* stands for effects that demonstrate results of innovative activity in business (European Commission (2015)). SII index ranges from 0 to 1, however, the closer the index value to 1, the higher the innovativeness level of a given country's economy. Estimated SII value gives basis for classifying EU countries into four groups according to the level of economy innovativeness.

In 2013 the European Commission introduced additional index – *The Innovation Output Indicator* focusing on measuring innovative activity output. It emerged in response to an objective formulated in the Europe 2020 Strategy, concerning increased expenditure on R&D. The new indicator allows the assessment of the progress of member states in achieving established benchmarks. Simultaneously, it supplements Innovation Union Scoreboard (IUS) and Summary Innovation Index (SII). The new indicator suggested by the European Commission is based on four elements significant in terms of EU policy: (1) European technological innovations are measured by the number of patents granted, (2) Employment level in knowledge-intensive activities, expressed by percentage of total employment, (3) Competitiveness of knowledge-intensive products and services, (4) Employment level in fast-growing enterprises in innovative sectors (European Commission (2013)).

3. Description of empirical research

3.1. Research objective

The research aims at working out a synthetic measure estimating country's innovation potential – CIP. The authors' main objective is reducing the primary set of diagnostics variables and simultaneously distinguishing variables which best describe innovation potential of particular member states. The goal shall be achieved by application of various yet complementary methods of multidimensional statistics. The specific objective of the paper is linear ordering of EU countries according to their innovation level based on *CIP* synthetic measure. The following ranking will be compared with ratings based on recognized *Summary Innovation Index and Global Innovation Index*.

[5] SII reaches values from 0 (low innovativeness) to 1 (high innovativeness).

3.2. Description of diagnostics indicators

Data presented in the article come from the European Statistical Office – Eurostat. For the analysis of innovative potential of EU member states, 25 variables were selected in total, and categorized into four different areas of analysis, i.e. investment expenditure, education, labour market, effects. It is a common practice to make clusters of data into specific areas of analysis when building innovativeness ratings (compare *SII* and *GII*). Making the first selection of features for the analysis of the innovative potential of economies, the authors aimed at creating a unique personal attitude, acknowledging the outcomes achieved in the discussed field at the same time. Therefore, two rules were applied when selecting variables: at least two variables representing each distinguished area are also included in *SII* and/or *GII* (1), each area of the analysis is dominated by variables suggested by the authors of the research (2). Moreover, the authors suggest that when creating innovation ratings too little attention is given to society treated as part of the process of creating innovation. Society presents a starting point for creating innovation, its needs and deliberate pursuit of applying innovation are the driving force. This is why the analysis included variables illustrating the employment level, education level, society's interest in information and communication technologies. This particular aspect makes the approach closer to that presented in *GII* rather than in *SII*. Nevertheless, the authors believe that *Global Innovation Index* sees innovativeness from a too broad perspective. As a result, real advantages of particular economies become hard to establish. Furthermore, the aim of multivariate analysis should be to identify only those determinants that are crucial for socio-economic growth through innovation. The subjects of the analysis include EU-28 countries, also referred to as analysis units. For the purpose of estimating EU countries' innovative potential, each presented diagnostic variable is treated as a stimulant, which means that the growth of the value influences the analysed phenomenon in a positive way. In constructing an index of a country's innovation potential, *Global Innovation Index* (Dutta et al. (2015) and *Summary Innovation Index* (European Commission (2015)) methodology were used as a framework for selecting and placing the diagnostic variables into four areas (investment, education, labour market, effects). As a supplement, policy recommendations of the OECD Working Paper (Freudenberg (2003)) and OECD Growth Project (OECD (2001)) were applied. The classification scheme consists of four core areas that combine between five to eight diagnostic variables. To analyse EU countries' innovative potential the initial set comprises 25 indicators, mostly derived from the statistical office of the European Union – Eurostat databases (http://ec.europa.eu/eurostat) – see Table 1. The first core area sees investment expenditure both from public and private perspective. The second core area aggregates variables related to the educational achievements of a country. In the third area labour market is presented. The last area looks at effects of innovative activities including patents, community designs and trademarks, as well as a share of innovative enterprises.

Table 1. Initial and final dataset

Investment expenditure	**X1**	Public R&D expenditure as % of GPD;	**Labour market**	**X2**	Employment rate in population aged 20-64;
	X7	Total public expenditure on education as % of GPD;		**X3**	Employment in technology and knowledge-intensive sectors as a percentage of total employment;
	X13*	Business enterprises R&D expenditure as % of GPD;		**X12**	Percentage of SMEs (10-249 employees) that employed ICT/IT specialists;
	X17	Percentage of households with a broadband Internet connection;		**X14***	Total R&D personnel as a percentage of total employment;
	X22*	Percentage of households with Internet access;		**X5***	Percentage of individuals aged 25-64 using computer at least once a week but not every day;
Education	**X4**	Percentage of population aged 30-34 with tertiary education degree;		**X10**	Percentage population/individuals aged 25-64 using Internet at least once a week including every day;
	X6	Students (ISCED 1_6) aged 15-24 – as % of a corresponding age population	**Effects**	**X8***	Patents granted by United States Patent and Trademark Office per 1 million inhabitants;
	X11	Percentage of individuals aged 25-64 with competences in terms of using computers (at least 5 out of 6 activities listed in the research);		**X9**	Patents filed to European Patent Office per 1 million inhabitants;
	X15	Percentage of individuals aged 15-24 having participated in tertiary education (ISCED 5-8) (formal education, ISCED 5-8);		**X19**	Community trade mark (CTM) registrations per 1 million inhabitants;
	X16	Percentage of individuals aged 25-64 participating in non-formal education and training;		**X20***	Innovative enterprises (including enterprises with abandoned/suspended or ongoing innovation activities) as a percentage of total number of enterprises;
	X18	Graduates (ISCED 5-6) in science, mathematics and technology aged 20-29 per 1000 citizens;		**X21***	Community design (CD) applications per 1 million inhabitants;
	X23*	New doctorate graduates (ISCED 6) per 1 million inhabitants;		**X25***	SMEs introducing product or process innovations as percentage of SMEs;
	X24	Graduates (ISCED 5-6) in science, mathematics and computing, engineering, manufacturing and construction as percentage of all graduates;			

Note: Implementation of the proposed statistical procedure resulted in reduction of 9 variables from the initial dataset – see variables marked with "*".

Source: own elaboration based on data from the statistical office of the European Union – Eurostat – http://ec.europa.eu/eurostat

Building the database, the authors aimed at selecting most up-to-date data available in Eurostat. For this reason, variables used for the research come from different years since Eurostat database is not completed on a regular basis. In the case of 12 variables, the data regard 2014 (X_2, X_4, X_5, X_{10}, X_{11}, X_{12}, X_{15}, X_{16}, X_{17}, X_{19}, X_{21}, X_{22}), 6 variables represent 2013 values (X_1, X_3, X_{13}, X_{14}, X_{23}, X_{24}), another 5 – 2012 (X_6, X_9, X_{18}, X_{20}, X_{25}) and one – 2011 (X_7) and one – 2009 (X_8).

3.3. Methodology

Primary reduction of diagnostic variables was conducted by correlation and cluster analysis. Another reduction of diagnostic variables was based on factor analysis carried out by means of normalized Varimax rotation. For further analysis, variables included in selected factors were used. The presented approach concerns only several statistical methods whereas many others, being potentially helpful in selecting indicators and measuring innovativeness, are discussed widely in papers: Saisana & Tarantola (2002), Freudenberg (2003) or Cherchye et. al. (2005). As an added value of the paper, an analytical strategy, which allows for the application of a combination of complementary statistical methods, is adopted here. The selection of reducing a pre-defined set of variables, based on criteria that are meant to sort out redundant information, is a step forward to the conceptual model of innovativeness. The ultimate EU countries' innovativeness rating was created by applying a non-pattern linear ordering, with weighted and unweighted variant. Methods of reducing the set of diagnostics variables, the form of their weights used in the analysis and the proposition of some measures of the innovativeness can be treated as a new approach in the discussed area due to the fact that the existing methodology (connected with SII or GII) has a poor statistical justification[6]. The analyses were carried out by means of Statistica 8.0 and MS Excel.

4. Innovativeness determinants

4.1. Prselection of data

During the first stage, correlation analysis was applied to reduce the number of variables. From all pairs of variables where Pearson correlation coefficient was at least 0.95, it was the variable with a higher deviation coefficient based on standard deviation that was selected for further analysis. This procedure allowed elimination of co-linearity of explanatory variables, maintaining the most significant variables for the research at the same time. The exception is X_8 and X_9 pair of variables, which are strongly positively correlated, $(\rho_{8,9} = 0.95)$, being comparable in terms of variability. For further analysis, X_9 variable was chosen

[6] For instance, diagnostic variables are highly correlated and they have the same weights in the final index formula.

where data on EU countries are more up to date[7]. At this stage, variable X_{17} remained despite the high level of correlation with X_{10} and X_{22} variables ($\rho_{10,17} = 0.93$ and $\rho_{17,22} = 0.99$ respectively), assuming the access to broadband Internet an indirect determinant of changes in EU countries' innovativeness. Consequently, (compare Tab. 1) variables X_8, X_{20} and X_{22} were initially eliminated.

4.2. Reducing the number of variables by means of cluster analysis

Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters). A cluster can be described largely by the maximum distance needed to connect parts of the cluster (see Everitt (2011)). The next step towards dimensionality reduction of explanatory variables was clustering of variables[8]. The analysis was supposed to distinguish variables creating clusters, i.e. most similar variables (of the lowest value of Euclidean value). Clusters obtained through the lowest level of aggregation were later compared with correlation matrix identified a priori. It was concluded that X_{14} variable may be omitted without a significant loss of information, which results from the fact that its distance to X_{13} variable is the closest of the observed Euclidean distances[9], the variables represent a high correlation $(\rho_{13,14} = 0.83)$; in addition, variable X_{14} has a much lower volatility.

4.3. Reducing the number of variables by factor analysis

We used factor analysis to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors (see Child (2006), Thomson (2004)). Mathematically speaking, the object of factor analysis is a matrix of data containing n number of m variables $X = [x_{ij}]_{nxm}$, where $i = 1,2,\ldots, n$, $j = 1,2,\ldots, m$. As a result of transforming the value of variables by means of standardization formula we achieve variables of identical expected value (equals 0) and unit standard deviation: $Z = [z_{ij}]_{nxm}$. In this research, the reduced set of 21 variables underwent factor analysis. Principal components method was used to distinguish most relevant factors and corresponding factor loadings[10] (compare Walesiak (1996)). Yet, Varimax

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[7] In the case of variable X_8 the latest data come from 2009, while for X_9 variable – 2012.

[8] Generally, clustering is conducted for object class recognition by searching most homogenous clusters (of closest possible distance within the cluster and maximum possible distance to other clusters). It may be referred to as one of methods used for reduction of variables.

[9] Most homogenous clusters are built up by variables X_1, X_3, X_7, X_{13}, X_{14}, with variables X_{13} and X_{14} being closest by Euclidean distances.

[10] The factor loadings, also called component loadings, are the correlation coefficients between the cases (rows) and factors (columns). The squared factor loading is the percent of variance in that indicator variable explained by the factor. As a rule of thumb, in confirmatory factor analysis

normalized rotation[11] was introduced to maximize the variance of primeval factor loadings on variables. The following variables X5, X13, X31, X23 and X25 are removed from further analysis.

5. Results and discussion

The five-factor solution, implicitly identified by factor loadings, corresponds to a priori chosen classification scheme. This is confirmed by the fact that all the core areas (*Investment expenditure, Education, Labour market, Effects*) have their representatives in the final dataset, which comprises 16 variables. The reduction of the number of indicators from the predefined set is presented in Table 1. It is worth noticing that the statistical procedure proposed in the paper allowed for removing two variables from each of the core areas apart from *effects*, where reduction was made by 4 variables. In total, this makes the procedure more input than output oriented. In the case of synthetic measurement of innovative potential this is a very important issue.

The last stage of the analysis is establishing the EU countries' rating by their innovative potential. For this reason, the linear ordering method was applied, weighed and unweighted variant. Variables which serve as stimulators for innovativeness potential were first standardized, then two synthetic measures were created: M_{1k} (unweighted variant) and M_{2k} (weighted variant) for each country $k = 1,2,\ldots,28$, i.e.:

$$M_{1k} = \frac{1}{m}\sum_{i=1}^{m} z_{ik} , \tag{1}$$

$$M_{2k} = \frac{1}{\lambda}\sum_{i=1}^{m} \lambda_i z_{ik} , \tag{2}$$

where:

z_{ik} – standardized value of each variable (i) established for a specific country (k);
m – the number of other *analyzed* variables ($m = 15$), λ_i – weight related to i – the variable set. The i – th weight is the quotient where the numerator is an identified variance multiplied by the factor from which the variable is derived, divided by summary percentage of the variance identified by all factors, while denominator is the number of variables creating a particular factor, i.e. $\lambda = \sum \lambda_i$. The aggregation methods described in formulas (1) and (2) are widely

(CFA), loadings should be 0.7 or higher to confirm that independent variables identified a priori are represented by a particular factor.

[11] Varimax rotation is an orthogonal rotation of the factor axes to maximize the variance of the squared loadings of a factor (column) on all the variables (rows) in a factor matrix, which has the effect of differentiating the original variables by the extracted factor. Each factor will tend to have either large or small loadings of any particular variable. A varimax solution yields results which make the identification of each variable with a single factor as easy as possible.

used in linear ordering of objects (see Bąk (2015)). Further, in their report prepared for the European Commission, Saisana and Tarantola (2002) state that this approach is commonly applied and (…) "*The composite indicator is based on the standardized scores for each indicator which equal the difference in the indicator for each country and the EU mean, divided by the standard error.*" In fact, the presented method of aggregation makes the final index more robust when dealing with outliers.

The higher the synthetic factor value, the higher a given country's innovative potential. In the case of the 5 clusters of variables, they were assigned the following weights: 51.4%, 20.6%, 11.8%, 9.3%, 6.9%. Table 2 contains EU countries' rating by the descending values of M_{1k} and M_{2k} measures.

Table 2. EU countries' rating by innovative potential assessed by M_{1k} and M_{2k} compared to SII and GII results.

Country	M_{1k}		M_{2k}		SII		GII	
	Rank	Value	Rank	Value	Rank	Value	Rank	Value
Denmark	1	1.15	2	1.07	2	0.74	7	57.70
Finland	2	1.12	1	1.12	3	0.68	4	59.97
Sweden	3	0.92	3	0.96	1	0.74	2	62.40
Germany	4	0.69	4	0.82	4	0.68	8	57.05
Netherlands	5	0.47	5	0.44	5	0.65	3	61.58
United	6	0.39	7	0.39	7	0.64	1	62.42
Austria	7	0.37	6	0.4	11	0.59	9	54.07
Luxembourg	8	0.26	8	0.31	6	0.64	6	59.02
Estonia	9	0.22	9	0.29	13	0.49	11	52.81
France	10	0.21	10	0.27	10	0.59	10	53.59
Ireland	11	0.19	13	0.03	8	0.63	5	59.13
Slovenia	12	0.16	11	0.16	12	0.53	16	48.49
Czech	13	0.09	12	0.11	14	0.45	12	51.32
Belgium	14	0.07	14	-0.01	9	0.62	13	50.91
Malta	15	-0.06	17	-0.21	18	0.40	14	50.48
Spain	16	-0.09	16	-0.1	19	0.39	15	49.07
Portugal	17	-0.14	15	-0.09	17	0.40	17	46.61
Hungary	18	-0.27	20	-0.36	20	0.37	21	43.00
Lithuania	19	-0.3	18	-0.25	25	0.28	23	42.26
Slovakia	20	-0.33	19	-0.31	22	0.36	22	42.99
Italy	22	-0.45	21	-0.41	16	0.44	18	46.40
Latvia	21	-0.45	22	-0.46	26	0.27	19	45.51
Poland	23	-0.5	23	-0.47	24	0.31	27	40.16
Cyprus	24	-0.57	26	-0.66	15	0.44	20	43.51
Croatia	25	-0.58	24	-0.55	23	0.31	25	41.70
Greece	26	-0.63	25	-0.6	21	0.36	26	40.28
Bulgaria	27	-0.87	27	-0.91	27	0.23	24	42.16
Romania	28	-1.05	28	-0.97	28	0.20	28	38.20

Note: calculations carried out by means of Statistica 8.0 and MS Excel

Source: own elaboration based on data from the statistical office of the European Union – Eurostat – http://ec.europa.eu/eurostat

The next step was comparing the EU member states' ratings created by means of linear ordering with *Summary Innovation Index* as well as *Global Innovation Index* (compare Tab. 2). The convergence of all the ratings was assessed with Spearman correlation coefficients. We obtained all correlation coefficients over 0.9 although we observe differences between ratings for rank positions from the middle. High correlations are justified due to the fact that positions of the most innovative countries and these with the lowest innovativeness performance are not threatened regardless of the set of diagnostic variables – primary or reduced.

The applied statistical tools (correlation analysis, cluster analysis, factor analysis) enabled reducing the number of diagnostic variables from 25 to 16 (compare Tab. 1). In this way, the authors reached their primary objective of maximum reduction of the set of features and distinguishing those which best identify the analysed phenomenon. Factor analysis led to identifying five principal factors explaining almost 80% of the total variance of variables. It is worth noticing that the identified factors are of multidimensional nature, which relates to multi variable factors. It means that one factor comprises features covering various areas of analysis, i.e. investment spending, education, labour market and effects (compare Section 3.2). The obtained results are relevant to the ones presented in the literature, where innovativeness is described by means of sets of variables representing different areas. For instance, the first distinguished factor (identifying almost 40% of the total variance) includes both variables of the *investment spending* (e.g. variable X_1) or *labour area* (variable X_2), as well as of other areas: *effects* (X_9) or *education* (X_{16}). Similarly, the second and third factor consist of variables representing different analysis areas, i.e. variables from the second factor include: X_6 and X_{18} (*education*), X_{19} (*effects*), and variables from the third factor include: X_3 (*labour market*), X_7 and X_{12} (*investment expenditure*). It should be emphasized that next two one-element factors relate to *education* area. One may draw a conclusion that human capital is a significant factor in building economy's innovative potential (compare Wheatley (2001), Klingbeil (2008)). According to R. E. Lucas, one of the basic factors stimulating economic innovativeness is human capital, which leads to technological progress when combined with the size and efficiency of R&D investment (Lucas (1988)).

5. Conclusions

The purpose of the research was to check an alternative approach to the approach that prevails in studying innovative potential of selected economies. For this reason, the authors attempted to create a rating based on possibly narrowest yet carefully selected set of diagnostic variables. A comparative analysis of the authors' rating and the rating based on *SII* lead to important conclusions on the ultimate assessment of EU countries' innovative potential. There is a great deal of convergence between authors' and *SII* rating, especially when it comes to top (Denmark, Finland, Sweden) as well as bottom positions (Bulgaria, Romania), which is confirmed by high rank correlation coefficients established for comparative ratings. Central positions in the ratings reveal major differences (Tab. 2). As some contrast, the proposed rankings differ from the GII rating, especially in the case of top 9 countries (for instance, *GII* evaluates the United Kingdom as a winner while this country is ranked 6th or 7th in other rankings). The proposal of the new innovativeness measure and the fact that linear ordering for the EU member countries with *CIP* index is convergent with the rating based on *SII* is to provide additional support for the adopted strategy. Further, the statistical procedure applied in the article may serve as a tool supporting creation of innovativeness conceptual framework and the initial selection of indicators. Nevertheless, the research outcome confirms a commonly shared view that the methodology of innovativeness assessment requires further research.

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