Is Romania a Favourable Environment for the Development of Knowledge-Based Organizations?

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Abstract

The Europe 2020 Stategy enhances the European Union's efforts to achieve sustainable economic growth, by transforming the economies of the member states in knowledge-based economies. This strategy aims at five major objectives that relate to unemployment, research and development, energy, education, poverty and social exclusion. Using the 8 indicators which measure these developments, this article aims to achieve an informational synthesis with a tolerable loss of information and to obtain an aggregate indicator, which will help at a graphical representation or a hierarchization of the countries analyzed.

Using the Principal Components Analysis, we used the values of the 8 indicators registered in the EU countries, plus Switzerland, Norway and Iceland, in 2010; two indicators that give about 95% of initial information have been found and it now becomes possible to rank the countries in terms of their evolution towards the stage of a knowledge-based economy. Thus, we get the answer to the question-title, discovering Romania's position in the European landscape of knowledge-based economies, by having achieved the ranking of the countries.

Keywords: *Europe 2020 strategy, Principal Components Analysis, knowledge-based economy, Romania*

JEL classification: C82, O11, 052

Introduction

Knowledge management and knowledge-based economies are a central theme among specialists, both at microeconomical and macroeconomical level. The knowledge revolution (Nicolescu & Nicolescu, 2005) and the transformation of the informational society into a human resources centered society (Geisler & Wickramasinghe, 2009), actually, have sequentially lead to what we know and refer to today as the knowledge-based economy. Among organizations, there are famous examples of companies that have created communities of practice or promote knowledge sharing, such as Ford Motor Company, Xerox Corporation or IBM Credit Corporation (Stefanescu et al., 2009). Our focus in this paper is towards the macroeconomic level, since we wish to find Romania's position in the European landscape of knowledge-based economies, by conducting a ranking of the countries from this point of view. Our country's position will hint us to whether we can provide a favourable environment for knowledge organizations or not.

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The European Union officially acknowledges the importance of the knowledge-based economy by outlining the Lisbon Strategy, in March 2000. The European Council in Lisbon settles the development plan of the economy of the European Union (EU) for the following 10 years, outlining the Lisbon Strategy, which aimed at turning the EU into "the most competitive and dynamic knowledge-based economy in the world capable of sustainable economic growth with more and better jobs and greater social cohesion" (Lisbon European Council, 2000). Around the middle of the implementation interval, information concerning the progress evaluation of the member states was revealed. The Lisbon Agenda may appear as a luxury for Romania at the moment", finds a study (Group of Applied Economics, 2004) former to the evaluation of the strategy. It was the first time that significance was officially granted to knowledge and the appearance of the knowledge based-economy was acknowledged, but it was obvious that Romania was not ready to complete the transition in 2004. Even nowadays, 8 years later, in Romania almost 20% of SMEs have never heard of the concept of knowledge based economy" and only about 45% think they are familiar with the concept (Ceptureanu et al., 2012).

Therefore, by 2010, since the objectives of the Lisbon Strategy were not accomplished (and not just in Romania's case), the European Commission proposes the Europe 2020 Strategy, as an extension of the previous one. In addition to the Lisbon Agenda, Europe 2020 is not only a strategy for the transformation of the economies into knowledge-based economies, although this goal is still pursuit, but this strategy also represents a solution for ending the financial-economic crisis which entered into force during 2008-2009.

The goal of the Europe 2020 Strategy is to obtain a growth that is: smart, through more effective investments in education, research and innovation; sustainable, thanks to a decisive move towards a low-carbon economy; and inclusive, with a strong emphasis on job creation and poverty reduction" (European Commission, 2010). This goal is to be attained by means of 5 general objectives chosen by the European Commission (2010):

- Employment rate: at least 75% of the 20-64 year old population should be employed;
- Research & Development (R&D): at least 3% of the EU's Gross Domestic Product (GDP) should be invested in R&D;
- Climate change:
  - Reducing greenhouse gas emissions by 20% year base 1990;
  - Increasing the share of renewables in final energy consumption to 20%;
  - Obtaining at least a 20% increase in energy efficiency;
- Education:
  - Reducing school drop-out rates to less than 10%;
  - At least 40% of the 30-34 year old population having completed third level education;

- Poverty and social exclusion: at least 20 million fewer people at risk of poverty or social exclusion.

These objectives have also been transposed in national targets, in order to adapt them to the special circumstances of each country, but, generally, they are found between the same boundaries. Using the recorded values for these objectives in the EU's countries (and another 3 random countries from Europe: Switzerland, Norway and Iceland) in the year 2010, this paper attempts to make a ranking of the countries, in order to explore their positions. Since it is practically impossible to rank them according to 8 indicators (measuring 5 general objectives, two of which have another two/three sub-targets), we need to use a quantitative statistical-mathematical method. This is the Principal Components Analysis, a method which allows us to make an informational synthesis which we require in order to obtain an aggregate indicator, also holding on to almost all the initial information. When we obtain an aggregate indicator (or even two or three), the space dimensionality is sufficiently reduced so that we can graphically represent or order the elements we are studying, which is exactly the purpose of this paper.

1. Research methodology

The method which allows us the informational synthesis in order to obtain an authentic aggregate indicator is the Principal Components Analysis (PCA).

Principal Component Analysis (PCA) is an explorative technique used for the integration of the data. The main advantage of the method is that it allows the rephrasing of the original variables by reducing the number of dimensions, without much loss of information" (Smith, 2002). The initial set of data usually has numerous deficiencies, which include redundancy or high dimensionality of the data, hence the difficulty to arrange the cases (Ruxanda, 2001). The extremely important utility of the PCA shows here, the methods helping us to express the initial variables through a same number of new variables, called principal components - w_i; these principal components are uncorrelated with each other and they assume the entire amount of information contained in the original variables. Using various criteria, we will later choose how many of these new variables we want to keep for the analysis, losing only minimal information, but significantly reducing the dimensions of the mathematical space of the analysis.

We may express the problem in the following way:

$$W = \dot{\alpha}_1 x_1 + \dot{\alpha}_2 x_2 + ... + \dot{\alpha}_n x_n \qquad (1)$$

where W is the vector of the principal components; x_i is our data; $\dot{\alpha}$ is a scalar number. The question now is: what should be the value of $\dot{\alpha}_i$, so that w_n can assimilate the maximum amount of information from our initial vector of information X?

PCA may use the covariance matrix or the correlation matrix. In our case, we used the covariance matrix, this being the "classical" way. The logic of the analysis would have remained the same even if we has used the correlation matrix, the only difference being that in the second case we would have processed standardized data.

The covariance matrix is the matrix which has the variance of the original variables on the main diagonal and the other elements are the covariances of the variables that are placed on that line and column. Once we have the covariance matrix, it can be demonstrated (Dedu et al., 2009) that the $\dot{\alpha}$ vector which defines the principal components vector (W) is an eigenvector of the matrix, following the formula:

$$MX = \dot{\alpha}X \tag{2}$$

where $\dot{\alpha}$ is a number called "eigenvalue", M is any matrix, and X is the initial vector of data.

Thus, we can say that "PCA is the simplest of the true eigenvector-based multivariate analyses" (Wikipedia, 2012). Further on, the question is that of choosing which of the eigenvectors of the matrix (as it has a number of eigenvectors equal to its dimension) we use to define the principal components, w_i. This is where the dimensionality reduction happens, because we shall keep only the first *k* principal components for the analysis, the ones with the biggest variance, depending on the needs of our analysis.

Two important results from the PCA are of interest now. The first one is the principal scores matrix. The principal scores represent coordinates of our initial objects, but in the new space with reduced dimensionality, where the principal components were defined. The second important matrix is the factor matrix. This is, itself, also a correlation matrix, but between the original variables (in lines) and the principal components retained for analysis (in columns). Thus, this matrix helps to interpret the principal components, specifically allowing us to give a name and explanation for them, based on the correlation of each principal component with the original variables.

Next, we show how the PCA helps us find the hierarchy we want. As mentioned above, we use data from year 2010, registered in the 27 EU member state, plus Switzerland, Norway and Iceland, randomly chosen, to reach a total of 30 countries. The 8 variables are the measure for each country for the targets in the EU2020 strategy and they have the following meanings:

- Employment Rate (EmplR): expresses the employment rate in each country (%);
- Gross Expenditure on Research and Development (GERD): the percentage of GDP spent on R&D (%);
- Greenhouse Gas Emissions (GrGE): expressed correlated to the value from the year 1990, considered to have the value 100;

- Renewable Energy (RenEn): expresses the share of renewable energy in the gross final energy consumption (%);
- Primary oil consumption (TOE): a measure for the real energy comsumption, expressed in "tones of oil equivalent";
- Early Leavers from Education (ELvEd): percentage of population aged 18-24 leaving school early (%);
- Tertiary Education Attainment (TrEdA): percentage of population aged 30-34 with tertiary education (%);
- People at Risk of Poverty or Social Exclusion (PrP/SE): expressed as a percentage from the total population of the country (%);

The data has been retrieved from the Eurostat website (European Commission, 2012). We seek to compose an overall preview of a potential hierarchy of the European countries, considering the values registered on the variables above. The Principal Component Analysis (PCA) aims to identify a synthetic indicator, which is not characterized by redundancy and contains the maximum of information from the 8 original variables. For data processing we used the software Statistics 8 and, when necessary, Microsoft Office Excel 2007. We chose data aggregation using the covariance and unbiased version, with *(n-1)* degrees of freedom, where *n* is the total number of observations or cases.

2. Results and interpretation

After running the software on the cases (countries) and variables (indicators), we find much useful information for analysis. The most relevant results for the purpose of this paper are the ones we have chosen to present next: the covariance matrix of variables, the eigenvalues of the initial variables, the factor matrix, which shows the correlations between the variables and the principal components, as well as the principal scores matrix.

2.1 Covariance matrix of variables

Table 1, as mentioned above, shows the covariance matrix of the variables. This is of interest for our study, because it shows a big picture of the 8 variables we choose to include in the analysis. On the main diagonal of the matrix we have the variances of the variables; all the other elements represent covariances of the elements of the line / column. The covariances have very different values, widely spread, fact which shows us an increased level of complexity of this problem. This same fact may, as well, be considered a mathematical justification for approaching this issue concerning the reduction of the space dimensionality and, implicitly, complexity reduction.

Table 1. Covariance Matrix of Variables

Variable	EmplR	GERD	GrGE	RenEn	TOE	ELvEd	TrEdA	PrP/SE
EmplR	40.02	2.13	52.23	21.06	18.45	-10.92	31.19	-32.28
GERD	2.13	1.03	-0.15	6.48	24.34	-1.64	2.87	-3.57
GrGE	52.23	-0.15	905.82	-84.07	-191.8	99.55	62.24	-107.9
RenEn	21.06	6.48	-84.07	205.3	-155.6	-3.45	14.17	-3.03
TOE	18.45	24.34	-191.8	-155.7	6114.04	21.41	-2.19	-68.29
ELvEd	-10.92	-1.64	99.55	-3.45	21.41	57.01	-16.99	7.45
TrEdA	31.19	2.87	62.24	14.17	-2.19	-16.99	101.35	-23.9
PrP/SE	-32.28	-3.57	-107.9	-3.03	-68.29	7.45	-23.99	60.8

Source: author, using software Statistica 8

2.2 Eigenvalues of the original variables

Table 2 introduces the specific results of the PCA. In the table we find the eigenvalues of our variables. Considering that the variance, generally, shows us the amount of information we can retrieve (Ruxanda, 2001), we can see that the first eigenvalues contains 81,84% of the initial information found in the 8 target-variables of the EU2020 strategy. This is a very important outcome. Practically, we have expressed through one single indicator the level where each country stands from the point of view of the European strategy's objectives, with a very small and tolerable informational loss. The mathematical space dimensionality has been reduced from 8 variables to only 1 new variable, with less than 20% informational loss.

Table 2. Eigenvalues of the original variables

	Eigenvalue	% Total Variance	Cumulative Eigenvalue	Cumulative %
1.	6125.907	81.83822	6125.907	81.8382
2.	942.420	12.59013	7068.327	94.4284
3.	206.421	2.75765	7274.748	97.1860
4.	118.954	1.58915	7393.701	98.7751
5.	53.609	0.71618	7447.310	99.4913
6.	24.249	0.32395	7471.559	99.8153
7.	13.373	0.17865	7484.932	99.9939
8.	0.454	0.00607	7485.386	100.0000

Source: author, using software Statistica 8

Now, if we used the principal scores matrix, we could already make an order of the countries and see what position do each of them hold. But we can be much more rigorous an continue the analysis, by holding on to two principal components. Table 2 also tells us that the first two eigenvalues hold 94,43% of the initial information, which is extremely good considering that we are now in a new two-dimensional space, easy to understand, analyse and plot.

2.3 Factor matrix

Proceeding with the analysis with two principal components, we look at Table 3, which hold the factor matrix, helping us in naming the principal components, so that we can better understand their meaning. The first principal component is strongly negatively correlated to TOE. Therefore, we seek a general name, in a way opposed to the significance of the TOE indicator; if we assume that a big energy consumption (big TOE) means we have a strong, economically relevant developed country, that the new factor could be named "Irrelevancy Factor" or, metaphorically, "Shame Factor", because a small value of it is desirable. The second principal component is strongly positively correlated to GrGE, which means we could call the factor "Environmental Concern".

Table 3. Factor – Variable Correlations

Variable	Factor 1 - "Shame Factor"	Factor 2 - "Environmental Concern"
EmplR	-0,033137	0,291471
GERD	-0,304916	0,014764
GrGE	0,093626	0,994091
RenEn	0,140611	-0,245189
TOE	-0,999916	0,011947
ELvEd	-0,030393	0,437284
TrEdA	0,005802	0,224808
PrP/SE	0,106441	-0,490597

Source: author, using software Statistica 8

2.4 Principal scores matrix and the aggregate indicator

In Table 4 we find the principal score for our cases (the countries), that is the values we can use for a graphical representation in a two-dimensional space, based on 94,43% of the information from the 8 initial indicators. As mentioned earlier, we could only use one principal component and show the order of the countries based in 81,84% of the initial information. Still, in order to be rigorous, we hold on to two principal components for the analysis. Next, we need to "compose" an aggregate indicator of the two factors retained for analysis, so that we can afterwards show the hierarchy of the countries. First, we will use a formula (Ruxanda, 2001) which is based on the informational content of each factor:

$$Ci_{(a)} = var(w_a)/var_{cum} \quad (3)$$

where $Ci_{(a)}$ is the coefficient of importance for factor *a*, $var(w_a)$ is the variance of principal component *a* and var_{cum} is the cumulative variance of the (two) components held for the analysis. The coefficients of importance are weighted, so their sum is 1 and we shall have one coefficient for each principal component. With the formula above, we obtain these values: 0,87 for the first principal component and 0,13 for the second principal component. The following step is to "compose" the aggregate indicator of the principal components, using the coefficients of importance calculated above:

$$RI = 0,87*w_1 + 0,13*w_2 \quad (4)$$

where RI is the aggregate indicator and w_1, w_2 are the principal scores, found in the 2nd and 3rd columns of Table 4.

Table 4. Factor coordinates of cases (countries) and the ranking of the cases

Country	Factor 1	Factor 2	Rank (aggregate) Indicator	Rank
Belgium	2.625	1.0003	3584.14	1. Germany
Bulgaria	38.176	-41.8822	-21233.74	2. France
Czech Republic	13.801	-21.8547	-16404.24	3. U. K.
Denmark	37.718	-4.4691	27004.83	4. Italy
Germany	-250.065	-9.0616	-229336.63	5. Romania
Estonia	49.418	-44.1092	-14348.3	6. Poland
Ireland	42.458	17.3444	59486.18	7. Lithuania
Greece	29.713	18.1379	49429.58	8. Latvia
Spain	-65.119	35.8512	-10046.97	9. Bulgaria
France	-199.620	7.5539	-163849.33	10. Czech R.
Italy	-108.977	6.7873	-85986.5	11. Estonia
Cyprus	56.593	73.7892	145161.87	12. Spain
Latvia	51.212	-52.5115	-23710.51	13. Slovakia
Lithuania	49.068	-53.0696	-26301.32	14. Hungary
Luxembourg	51.825	1.9696	47648.23	15.Netherlands
Hungary	31.913	-24.8591	-4552.52	16. Sweden
Malta	57.440	56.0887	122888.11	17. Belgium
Netherlands	-14.759	9.3422	-695.47	18. Denmark
Austria	24.910	12.1231	37431.73	19. Finland
Poland	-40.283	-4.5042	-40901.67	20. Austria
Portugal	35.287	23.0356	60645.97	21. Norway
Romania	21.608	-48.6484	-44443.96	22.Switzerland
Slovenia	50.287	10.5606	57478.47	23.Luxembourg
Slovakia	38.745	-30.5275	-5977.6	24. Greece
Finland	22.260	11.7151	34595.83	25. Slovenia
Sweden	8.157	-3.7544	2215.87	26. Ireland
United Kingdom	-148.436	-8.5246	-140221.3	27. Portugal
Iceland	57.579	39.5235	101474.28	28. Iceland
Norway	26.772	11.7690	38591.34	29. Malta
Switzerland	29.694	11.1844	40373.5	30. Cyprus

Source: author, using software Statistica 8 and Microsoft Office Excel 2007

After calculating the aggregate indicator for each country (column 4, Table 4), we just have to arrange the countries accordingly. In the 5th column of Tabel 4 shows the place occupied by each country in the ranking, in respect to where they stand as far as the EU 2020 objectives are concerned. This represents, actually, precisely the ranking we wanted. Very important: we need to state that the first place will we appointed to the country with the smallest value of the aggregate rank indicator (RI).

A closer look at the last two columns of the table tells us that the top three countries would be Germany, France and United Kingdom, followed by Italy, Romania and Poland. In other words, these are the countries where the attainment of the EU2020 strategy objectives is going well, that is the countries are on the right track toward achieving the status of knowledge-based economies, acording to the European strategy.

The fact that Romania came out on the 5th position is surprisingly good, because, according to Nicolescu et al. (2011) the Romanian management, as compared to the management that is predominant in the European Union is inferior"; on the other hand, this can induce the ideea that the development perspectives of our country are positive and favourable for a future sustainable socio-economical growth. By all means, it is obvious that Romania still has a lot of effort to put into this direction, especially in the social domains, such as the employment rate, the early school leaving rate and the number of people at risk of poverty or exclusion" (European Commission, 2012). In a wider context, we also know that renewable energy sources have great potential in our country" (Pîrlogea, 2011), but, on the other hand, Romania has made limited progress in 2011" (European Commission, 2012); all in all, it is advised to enhance the efforts for the delivery of the Europe 2020 strategy as the basis for any new growth initiative". Fortunately, according to some specialists (Ceptureanu et. al, 2012) many companies in the Romanian business environment have understood the importance of knowledge management in increasing the efficiency and effectiveness of management, among other things, and this, on a general level, will contribute to the evolution of the entire country and also the indicators of the Europe 2020 strategy.

Conclusions

The Principal Component Analysis undertaken above has led to two main results. The first result is the informational synthesis of the 8 original indicators into 2 principal components that contain about 95% of the initial information. The two principal components are the Irrelevance Factor, metaphorically called "Shame Factor", with a low desirable value, and the Environmental Concern factor, with a desirable high value. The second important result is the development of an aggregated indicator of the attainment level of the EU2020 strategy's objectives, which showed the hierarchy and allows the graphical representation of the 30 companies that we have analyzed. The literature in this field does not contain, at the moment, any indicator presented and expressed in this way, referring mainly to knowledge-based economies, nor are there any economic models that allow such as ordering of the countries, as it may be done with such an aggregate indicator. Therefore, the use of such a methodology may be extremely useful in identifying or, at least, sensing the evolution of an economy towards the status of a knowledge-based economy, methodology which is founded on a quantitative and statistical base.

Also, other conclusions may be drawn from the present hierarchy. The fact that Germany and France are the leaders should direct our attention towards them as examples to be followed; the surprisingly 5th place of Romania should not steer up too much enthusiasm that would soften the path of development, because our country still has a long way ahead of it, even if we are heading in the right direction. All in all, it is safe to say that Romania has potential to become a favourable environment for the development of knowledge-based organizations.

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