# AN APPLICATION OF PRINCIPAL COMPONENT ANALYSIS TO INTERNATIONAL COMPARISON OF ECONOMIC ACTIVITIES

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**Abstract**

There is an acute need for a suitable composite measure of national economic performance insensitive to subjective preferences of different attributes of a multidimensional social pattern. The question is how to aggregate partial measures using appropriate weighting coefficients that will not rely on subjective judgments concerning their relative significance. In line with a number of studies we propose a rather simple but comprehensive approach based on principal component analysis widely used in multidimensional statistics. Though the first principal component or the set of principal components are known to be used as an aggregate economic indicator, this approach usually implies significant loss in variance of initial factors. However, we argue that the problem has a rather straightforward solution. The whole set of principal components weighted by the corresponding proportions of explained variance can serve as a universal "natural" aggregate measure of various types of economic activities. The proposed methodology is applied to evaluate the national competitiveness and to build the corresponding ranking of the countries in Eurasian region.

**Key words:** principal component analysis, international competitiveness, country ranking

**JEL Code:** C01, F00

## Introduction and literature review

Nowadays competitiveness is one of the most frequently analyzed economic category. There is no unique approach to qualification and measurement of this complex notion (Aiginger, 2006). National competitiveness is determined mainly by: a country's ability to achieve high sustainable economic growth rates; the level of factors' productivity; the ability of national companies to compete successfully in international and domestic markets.

Competitiveness can be considered at micro and macro level. Competitiveness at the micro level can be traced by dynamics of market share, technological advances and quality of output. Competitiveness at the macro level integrates economic growth, quality of life and aggregate productivity.

M. Porter's idea (1998) that macroeconomic efficiency is the basis of national competitiveness can be regarded as the origin of Global Competitiveness Index (GCI) by World Economic Forum (WEF).

WEF analysis is based on 12 factors of productivity (pillars). National competitiveness is ranked according to overall economic performance (social and international relations), the role of state and institutional framework. World Economic Forum identifies such factors as institutions, infrastructure, financial, technology, labor and macroeconomic situation as key elements of national competitiveness.

National economic performance is a multidimensional characteristic that comprises a variety of indicators reflecting different social processes and phenomena. In order to compare the results achieved by different countries one has to construct a kind of a composite indicator aggregating specific measures of a variety of social patterns. Despite of a huge set of studies and a continuous discussion still there remains a need for a suitable measure that will not be sensitive to subjective preferences concerning the relative significance of specific social and economic features. The question is how to aggregate partial measures using appropriate weighting coefficients that will not rely on subjective judgments.

In line with a number of studies that try to avoid any references to expert assessments in the choice of the weighting coefficients in construction of a composite indicator (see, for instance, (Barrington-Leigh and Escande, 2018), (Pérez-Moreno, Rodríguez and Luque, 2016), (Poledníková and Melecký, 2017), (Thore and Tarverdyan, 2016)) we propose a rather simple but comprehensive approach based on principal component analysis widely used in multidimensional statistics.

We use principal component analysis (PCA) which is a common statistical technique employed to reduce a larger set of correlated variables into a smaller set of uncorrelated variables (principal components) that account for most of the variation in the original dataset.

Application of principal component analysis to index numbers design has a rather long history. The typical motivation was to evaluate a general level of economic activity (Peters and Butler, 1970) and to obtain a universal measure of economic activity – a kind of genuine quality of life index – that will avoid the shortcomings of per capita GNP (Ram, 1982).

Nowadays PCA is broadly used in construction of regional and national competitiveness rankings. The essence of this approach can be found in (Aivazian and Mkhitarian, 2001), (Aivazian et al., 2006). The authors use the first principal component as an aggregate indicator of economic performance. This approach is characterized by transparent and accurate methodology that is based solely on statistical data, excludes any expert estimates and guarantees reliability of the resulting indicators. A variation of this methodology with an intention to incorporate an information transfer approach is given by (Zhgun, 2017).

Unfortunately the first principal component is not an appropriate measure in a typical situation when the proportion of total factors' variance explained by the first principal component is not sufficiently large. In this case one may use a number of the first principal components which together explain a major part of the factors' variance and apply either expert assessments or implicitly the shares of explained variance as weighting coefficients. Still this approach usually implies significant loss in variance of initial factors that is taken into consideration.

## Methodology, data and analysis

Principal component analysis is designed to reduce the dimension of variable space that characterizes a statistical object. Principal components form an orthogonal normalized system of linear combinations of original statistical variables that retains their total variation. Principal components are ranked in accordance with the share of comprised variance of the available data. Let $X = \{x_i\}_{i=1}^{n}$ be a vector of $n$ original variables that characterize economic performance of a number ($m$) of countries $\left(x_i = \{x_{ij}\}_{j=1}^{m}\right)$. Thus primary data forms a matrix $X = \begin{pmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{pmatrix}$. Denote by $\Sigma = \begin{pmatrix} \sigma_{11} & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \cdots & \sigma_{nn} \end{pmatrix}$ the corresponding covariance matrix. Note that the covariate matrix is invariant with respect to a fixed shift of primary data. So further on we consider centered data vectors: $Ex_i = 0$, $i = 1,\ldots,n$. Total variation of primary variables is given by trace of the covariance matrix $tr\Sigma$.

Denote by $l_k = \{l_{ki}\}_{i=1}^{n}$ the normalized vector of $k$-th component loadings $\left(l_k l_k^T = 1\right)$ and by $z_{kj} = \sum_{i=1}^{n} l_{ki} x_{ij}$ – the $k$-th component score for the $j$-th country. Principal component loadings form the matrix $L = \begin{pmatrix} l_{11} & \cdots & l_{1n} \\ \vdots & \ddots & \vdots \\ l_{n1} & \cdots & l_{nn} \end{pmatrix}$ of linear transformation of initial data into principal component scores: $Z = \begin{pmatrix} Z_1 \\ \vdots \\ Z_n \end{pmatrix} = \begin{pmatrix} z_{11} & \cdots & z_{1m} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nm} \end{pmatrix} = LX$, where $Z_k = \left(z_{k1},\ldots,z_{km}\right)$ is the $k$-th principal component vector.

Thus, the first principal component vector $Z_1 = (z_{11}, \ldots, z_{1m})$ solves the problem (Aivazian and Mkhitarian, 2001):

$$DZ_1 = D(l_1 X) = l_1 \Sigma l_1^T \to \max_{l_1}$$
$$s.t. \quad l_1 l_1^T = 1;$$

where $D(\cdot)$ denotes the variance of component scores. Here we take into consideration that the variables X are centered and $E(XX^T) = \Sigma$, thus $E(l_1 X)^2 = E(l_1 XX^T l_1^T) = l_1 \Sigma l_1^T$.

To solve the problem form Lagrange function $L_1 = l_1 \Sigma l_1^T - \lambda(l_1 l_1^T - 1)$, take its derivative with respect to $l_1$, and put it equal to zero: $\frac{\partial L_1}{\partial l_1} = 2\Sigma l_1^T - 2\lambda l_1^T = 2(\Sigma - \lambda I) l_1^T = 0$.

The first principal component loadings are an eigenvector of the covariance matrix:

$$(\Sigma - \lambda I) l_1^T = 0. \tag{1}$$

To solve equation (1) one has to use specific values of $\lambda$ that are given by the characteristic equation of the matrix $\Sigma$:

$$|\Sigma - \lambda I| = 0. \tag{2}$$

Multiply $l_1$ by (1) to get

$$DZ_1 = D(l_1 X) = l_1 \Sigma l_1^T = \lambda_1. \tag{3}$$

The covariance $(n \times n)$ matrix is symmetrical and positive definite, so equation (2) has $n$ real-valued nonnegative roots $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n \geq 0$ (characteristic roots, or eigenvalues of the matrix $\Sigma$). Thus the first principal components loadings are determined as the eigenvector that corresponds to the largest eigenvalue of the covariance matrix $\Sigma$. The following principal components $Z_k = (z_{k1}, \ldots, z_{km})$, $k = 2, \ldots, n$, use the other eigenvectors that correspond to successively smaller eigenvalues as the component loadings:

$$DZ_k = D(l_k X) = l_k \Sigma l_k^T = \lambda_k, \quad k = 2, \ldots, n. \tag{4}$$

Thus, principal component loadings are determined as eigenvectors of the covariance matrix $\Sigma$. The eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n \geq 0$ of the matrix $\Sigma$ are equal to the variance of the corresponding principal component scores $Z_1, Z_2, \ldots, Z_n$, where $Z_k = (z_{k1}, \ldots, z_{km})$ is the $k$-th principal component vector, $k = 1, \ldots, n$.

Note that often number of principal components that correspond to positive $\lambda_k$ is less than $n$.

The eigenvectors of the matrix are mutually orthogonal, thus matrix of principal components loadings constitutes an orthogonal transformation $\left(LL^T = L^T L = I\right)$ of the original data into the set of uncorrelated variables.

So one can represent equations (3)-(4) using a matrix notation: $L\Sigma L^T = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}$.

Since principal components are orthogonal this is their covariance matrix.

Total variance of principal components coincides with total variance of primary data:

$$\sum_{k=1}^{n} DZ_k = \sum_{k=1}^{n} \lambda_k = tr\left(L\Sigma L^T\right) = tr\left((L\Sigma)L^T\right) = tr\left(L^T(L\Sigma)\right) = tr\left(\left(L^T L\right)\Sigma\right) = tr\Sigma = \sum_{k=1}^{n} DX_k ,$$

thus the share of total primary data variance explained by the *k*-th principal component is

$$\rho_k = \frac{\lambda_k}{\sum_{k=1}^{n} \lambda_k} . \tag{5}$$

The first principal component score $z_{1j}$ is known to be used as an aggregate economic indicator for the *j*-th country. A modified principal component approach to construction of integrate economic indicators (Aivazian et al., 2006) takes

$$y_{1j} = \sum_{i=1}^{n} l_{1i}^2 x_{ij} \tag{6}$$

instead of $z_{1j}$ as an aggregate indicator of economic activity in international rankings. This approach is based on normalized property of component loadings: $l_1 l_1^T = \sum_{i=1}^{n} l_{1i}^2 = 1$. It allows to treat the weighting coefficients $l_{1i}^2$ as shares that reflect the impact of a primary variable $x_i$ on the resulting integrate score. This indicator retains units of measure of initial variables $x_{ij}$. Unfortunately this approach fails to explain total variation of the data.

The proposed generalized modified principal component approach consists in calculation of an aggregate measure of national economic activity as a weighted sum of all its principal component scores:

$$I_j = \sum_{k=1}^{n} \rho_k y_{kj} = \sum_{k=1}^{n} \rho_k \sum_{i=1}^{n} l_{ki}^2 x_{ij} = \frac{\sum_{k=1}^{n} \left( \lambda_k \sum_{i=1}^{n} l_{ki}^2 x_{ij} \right)}{\sum_{k=1}^{n} \lambda_k} . \tag{7}$$

The *k*-th modified principal component score

$$y_{kj} = \sum_{i=1}^{n} l_{ki}^2 x_{ij} \tag{8}$$

is a constituting element of the composite index here. These constituting elements $y_{kj}$ are weighted by the corresponding shares of explained variance $\rho_k$ so as to retain units of measure of the original variables $x_{ij}$.

There is no loss in variance of the considered data. The explaining capability of the proposed indicator (7) is extended to the total variance of initial variables.

Suppose that original data can be grouped into a number $(\theta)$ of subsets or pillars that reflect definite attributes of social and economic pattern:

$$X = \begin{pmatrix} \tilde{X}_1 \\ \vdots \\ \tilde{X}_\theta \end{pmatrix}, \text{ where } \tilde{X}_\alpha = \begin{pmatrix} X_{n_{\alpha-1}+1} \\ \vdots \\ X_{n_\alpha} \end{pmatrix} = \begin{pmatrix} x_{n_{\alpha-1}+1,1} & \cdots & x_{n_{\alpha-1}+1,m} \\ \vdots & \ddots & \vdots \\ x_{n_\alpha,1} & \cdots & x_{n_\alpha,m} \end{pmatrix}, \ 1 \le \alpha \le \theta,\ 1 \le \theta \le n.$$

The aggregate index $I_j$ is a linear transform of original data. It can be represented by a sum of linear transforms of the pillars that constitute original data:

$$I_j = \frac{\sum_{k=1}^{n}\sum_{i=1}^{n}\lambda_k l_{ki}^2 x_{ij}}{\sum_{k=1}^{n}\lambda_k} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n}\lambda_k l_{ki}^2 x_{ij}}{\sum_{k=1}^{n}\lambda_k} = \frac{\sum_{\alpha=1}^{\theta}\sum_{i=n_{\alpha-1}+1}^{n_\alpha}\sum_{k=1}^{n}\lambda_k l_{ki}^2 x_{ij}}{\sum_{k=1}^{n}\lambda_k},\ 0 = n_0 < n_1 < \cdots < n_\theta = n. \quad (9)$$

Thus, the resulting aggregate indicator can be decomposed into a sum of partial indicators $I_{j\alpha} = \sum_{i=n_{\alpha-1}+1}^{n_\alpha}\sum_{k=1}^{n}\lambda_k l_{ki}^2 x_{ij} \Big/ \sum_{k=1}^{n}\lambda_k$, that reflect the effect of definite pillars on general economic performance:

$$I_j = \sum_{\alpha=1}^{\theta} I_{j\alpha}\ . \quad (10)$$

The proposed methodology is applied to evaluate the national competitiveness and to build the corresponding ranking of the countries in Eurasian region.

We use the data for 76 countries of Europe and Asia ($j$=76) available in (Global Competitiveness Report, 2017). The indicators of competitiveness are grouped into 12 categories, the pillars of competitiveness ($\theta$=12), that represent three key determinants of development (subindices): fundamental factors (institutions $(\alpha = 1)$, infrastructure $(\alpha = 2)$, macroeconomic environment $(\alpha = 3)$, health and primary education $(\alpha = 4)$), factors of efficiency (higher education $(\alpha = 5)$, goods $(\alpha = 6)$, labor $(\alpha = 7)$ and financial $(\alpha = 8)$ markets efficiency, technological readiness $(\alpha = 9)$ and market size $(\alpha = 10)$) and innovation factors (business sophistication $(\alpha = 11)$ and R&D innovation $(\alpha = 12)$).

CDI uses an arithmetic mean to aggregate these pillars. The stage of development achieved by a country, as proxied by the country's GDP per capita and the share of raw materials exports, affects the weights assigned to the three subindices (Global Competitiveness Report, 2017-2018). Countries are classified into factor-driven, efficiency-driven and innovation-driven economies. A country may be also in transition from one stage to another. GCI attributes higher relative weights to those pillars that are more relevant for the economy given its particular stage of development.

We use 109 indicators of the GCI database for the year 2017-2018. There is an ambivalent representation of the data. A group of 81 indicators which represent mainly WEF's Executive Opinion Survey data are scaled from 1 to 7 (best). These indicators reflect qualitative aspects of competitiveness, such as: property rights; quality of roads; internet access in schools; effectiveness of anti-monopoly policy; reliance on professional management; quality of scientific research institutions and so on. There are two 2 complex indicators (domestic market and foreign market size indices) among them (Global Competitiveness Report, 2017-2018).

The other 28 indicators have different dimensions (e.g. strength of investor protection (0–10 (best)); fixed telephone lines/100 pop.; life expectancy (years); tertiary education enrollment (%) and so on). To make them compatible with the previous group we normalize them into the 1-7 range: $x_{ij}^{n} = 1 + 6\left(\dfrac{x_{ij} - x_{ij}^{\min}}{x_{ij}^{\max} - x_{ij}^{\min}}\right)$, if an indicator corresponds to the case "the more the better", or $x_{ij}^{n} = 1 + 6\left(\dfrac{x_{ij} - x_{ij}^{\max}}{x_{ij}^{\min} - x_{ij}^{\max}}\right)$, if the case is "the less the better". Here $x_{ij}^{n}$ is a normalized variable; $x_{ij}^{\max}$ and $x_{ij}^{\min}$ are correspondingly the maximum and the minimum value of initial indicator $x_{ij}$.

Imagine now that we handle with such normalized variables $x_{ij}^{n}$ instead of $x_{ij}$ in all the expressions (1)-(10) above.

## Results and discussion

We use Gretl to calculate principle component loadings for 109 initial variables. There are 74 principal component vectors with positive eigenvalues. So the PCA actually yields reduction of factor space dimension.

For each country we calculate the overall index of competitiveness $I_j$ by summing up modified principal component scores $y_{kj}$ weighted by the corresponding share of explained variance $\rho_k$. Besides, we obtain partial indices as the sums of weighted modified principal component scores for each of 12 data pillars. These sub-indices generate the country's rankings with respect to particular pillars. They provide a glimpse of the factors of competitiveness and of the potential to improve it.

For instance, Switzerland – the overall rating leader – ranks the first in macroeconomic environment, labor market efficiency, business sophistication and R&D innovation. Still it is the 3rd in technological readiness, the forth in infrastructure, health and primary education as well as in financial market development; the fifth in institutions, and only the 8th in higher education and training and the 9th in goods market efficiency. So it possesses a huge potential of competitiveness enhancement. If this potential is realized Switzerland could enhance its leading competitive positions on the global scale. We do not take into consideration its lower position in market size pillar as it could be hardly improved.

The sum of 12 pillar sub-indices gives the overall national competitiveness index $I_j$ and the country's ranking.

The generalized modified principal component (GMPC) ranking is represented by tab. 1. A country's number ($j$) here corresponds to its rank.

The comparison of GMPC and GCI rankings brings controversial results (tab. 1, fig. 1). For the first group of countries (ranks from 1 to 21) the position has turned out approximately the same, as in GCI, with exception of Germany (-6 positions) and Iceland (+6 positions). If we address the pillars indicators, Germany has got only the 23rd rank for health and primary education and the 29th rank for the goods market efficiency. On the other hand, Greece, for example, is placed at the 18th position for health and primary education, because it is characterized by tertiary education enrollment of more than 100% (namely 113,87%), as compared, for instance, to Germany that reports "merely" 68,2% enrollment. Unfortunately, enrolment has nothing to do with the quality of education. Anyway, this indicator has influenced the final result.

Controversial indicators in the GCR database may partially stand for the observed deviations in results. If the leaders are nearly the same, then we may guess that GCI ranking vulnerability accounts for data collection methodology and may doubt if peculiar pillar weights imposed to different countries in GCI are relevant.

It should be noted that the countries rating according to the first principal component yields approximately similar but still slightly different results (tab. 1). The deviations from the GMPC rating are within ±8 positions (India is the only exception: its PC1 rank would be 15 positions higher). The first principal component (PC1) explains 47,13% of total variation of original data, so it could not provide the same ranking as the GMPC analysis. The ranking based on PC1 neglects more than half of data scatter, so it may be considered only as a proxy for the comprehensive GMPC rating.

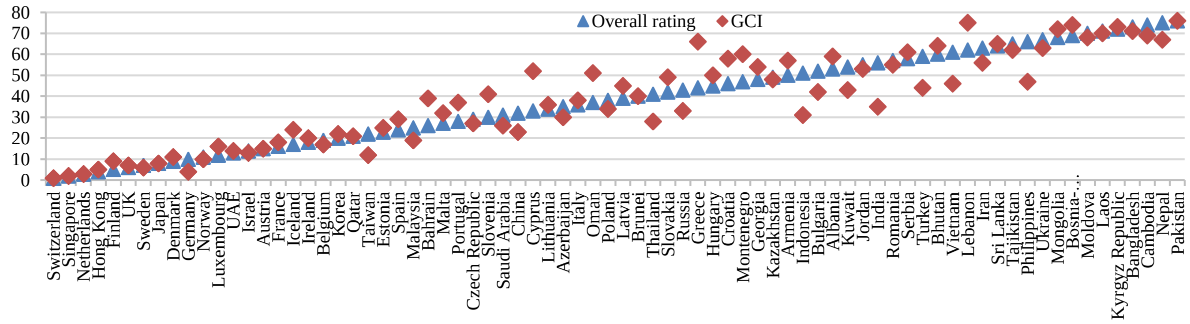
## Tab. 1. GMPC rating of Eurasian countries

| GMPC raking, j | Country | Institutions, α=1 | Infrastructure, α=2 | Macro-economic environment, α=3 | Health and primary education, α=4 | Higher education and training, α=5 | Goods market efficiency, α=6 | Labor market efficiency, α=7 | Financial market development, α=8 | Technological readiness, α=9 | Market size, α=10 | Business sophistication, α=11 | R&D innovation, α=12 | GCI rating (Eurasia) | Δ GCI rating | PC1 rating | Δ PC1 rating |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Switzerland | 5 | 4 | 1 | 4 | 8 | 9 | 1 | 4 | 3 | 27 | 1 | 1 | 1 | 0 | 1 | 0 |
| 2 | Singapore | 1 | 5 | 2 | 6 | 2 | 2 | 2 | 1 | 17 | 24 | 16 | 10 | 2 | 0 | 2 | 0 |
| 3 | Netherlands | 7 | 6 | 8 | 5 | 3 | 12 | 7 | 15 | 9 | 17 | 4 | 7 | 3 | 0 | 3 | 0 |
| 4 | Hong Kong | 6 | 1 | 10 | 22 | 13 | 6 | 4 | 3 | 11 | 22 | 9 | 26 | 5 | 1 | 7 | 3 |
| 5 | Finland | 2 | 18 | 16 | 1 | 1 | 10 | 15 | 2 | 7 | 45 | 15 | 5 | 9 | 4 | 4 | -1 |
| 6 | UK | 9 | 10 | 30 | 13 | 17 | 3 | 3 | 14 | 10 | 7 | 7 | 13 | 7 | 1 | 8 | 2 |
| 7 | Sweden | 10 | 16 | 5 | 12 | 10 | 18 | 13 | 7 | 5 | 28 | 6 | 3 | 6 | -1 | 5 | -2 |
| 8 | Japan | 14 | 2 | 40 | 7 | 23 | 27 | 19 | 13 | 12 | 4 | 2 | 2 | 8 | 0 | 6 | -2 |
| 9 | Denmark | 12 | 17 | 6 | 15 | 5 | 8 | 6 | 21 | 1 | 41 | 10 | 8 | 11 | 2 | 12 | 3 |
| 10 | Germany | 15 | 8 | 7 | 23 | 15 | 29 | 11 | 12 | 14 | 3 | 5 | 6 | 4 | -6 | 11 | 1 |
| 11 | Norway | 4 | 27 | 4 | 2 | 7 | 20 | 5 | 5 | 4 | 37 | 12 | 12 | 10 | -1 | 10 | -1 |
| 12 | Luxembourg | 8 | 11 | 3 | 9 | 51 | 13 | 10 | 6 | 2 | 55 | 14 | 14 | 16 | 4 | 9 | -3 |
| 13 | UAE | 3 | 22 | 19 | 28 | 38 | 1 | 9 | 11 | 20 | 20 | 18 | 21 | 14 | 1 | 13 | 0 |
| 14 | Israel | 20 | 19 | 26 | 11 | 22 | 14 | 16 | 10 | 23 | 42 | 11 | 4 | 13 | -1 | 17 | 3 |
| 15 | Austria | 18 | 13 | 17 | 18 | 16 | 19 | 22 | 24 | 22 | 31 | 3 | 11 | 15 | 0 | 15 | 0 |
| 16 | France | 26 | 3 | 24 | 21 | 21 | 47 | 34 | 19 | 13 | 6 | 13 | 16 | 18 | 2 | 16 | 0 |
| 17 | Iceland | 11 | 24 | 23 | 3 | 9 | 26 | 8 | 34 | 8 | 74 | 24 | 17 | 24 | 7 | 18 | 1 |
| 18 | Ireland | 16 | 21 | 18 | 14 | 6 | 7 | 14 | 47 | 21 | 33 | 19 | 18 | 20 | 2 | 20 | 2 |
| 19 | Belgium | 23 | 15 | 32 | 8 | 4 | 35 | 24 | 17 | 18 | 25 | 8 | 15 | 17 | -2 | 14 | -5 |
| 20 | Korea | 39 | 7 | 9 | 25 | 20 | 21 | 44 | 44 | 6 | 10 | 21 | 9 | 22 | 2 | 22 | 2 |
| 21 | Qatar | 13 | 38 | 15 | 27 | 42 | 5 | 17 | 8 | 26 | 39 | 23 | 19 | 21 | 0 | 19 | -2 |
| 22 | Taiwan | 25 | 9 | 11 | 61 | 11 | 16 | 28 | 9 | 27 | 15 | 20 | 23 | 12 | -10 | 21 | -1 |
| 23 | Estonia | 21 | 20 | 14 | 44 | 14 | 25 | 18 | 18 | 15 | 61 | 40 | 27 | 25 | 2 | 23 | 0 |
| 24 | Spain | 40 | 12 | 37 | 20 | 12 | 43 | 42 | 40 | 25 | 13 | 25 | 33 | 29 | 5 | 27 | 3 |
| 25 | Malaysia | 17 | 23 | 34 | 51 | 43 | 36 | 23 | 16 | 42 | 19 | 22 | 20 | 19 | -6 | 24 | -1 |
| 26 | Bahrain | 22 | 42 | 61 | 35 | 35 | 4 | 32 | 23 | 16 | 58 | 33 | 41 | 39 | 13 | 25 | -1 |
| 27 | Malta | 31 | 31 | 22 | 10 | 32 | 56 | 20 | 22 | 19 | 69 | 26 | 34 | 32 | 5 | 26 | -1 |
| 28 | Portugal | 35 | 14 | 48 | 31 | 24 | 28 | 36 | 64 | 30 | 40 | 35 | 29 | 37 | 9 | 28 | 0 |
| 29 | Czech Republic | 43 | 41 | 13 | 19 | 27 | 50 | 35 | 25 | 29 | 32 | 30 | 30 | 27 | -2 | 30 | 1 |
| 30 | Slovenia | 42 | 29 | 33 | 16 | 19 | 30 | 48 | 61 | 33 | 56 | 34 | 22 | 41 | 11 | 32 | 2 |
| 31 | Saudi Arabia | 19 | 40 | 42 | 45 | 34 | 32 | 65 | 28 | 45 | 12 | 29 | 36 | 26 | -5 | 29 | -2 |
| 32 | China | 32 | 28 | 12 | 52 | 44 | 68 | 26 | 30 | 51 | 1 | 27 | 25 | 23 | -9 | 31 | -1 |
| 33 | Cyprus | 37 | 36 | 51 | 29 | 36 | 15 | 27 | 72 | 24 | 67 | 38 | 43 | 52 | 19 | 37 | 4 |
| 34 | Lithuania | 41 | 32 | 35 | 40 | 28 | 42 | 45 | 42 | 28 | 51 | 39 | 35 | 36 | 2 | 35 | 1 |
| 35 | Azerbaijan | 28 | 30 | 68 | 63 | 58 | 24 | 12 | 36 | 41 | 49 | 32 | 32 | 30 | -5 | 33 | -2 |
| 36 | Italy | 64 | 25 | 41 | 17 | 33 | 62 | 59 | 68 | 38 | 9 | 17 | 24 | 38 | 2 | 36 | 0 |
| 37 | Oman | 24 | 55 | 44 | 42 | 55 | 22 | 51 | 26 | 53 | 47 | 49 | 65 | 51 | 14 | 34 | -3 |
| 38 | Poland | 51 | 37 | 25 | 30 | 31 | 38 | 52 | 41 | 44 | 16 | 48 | 44 | 34 | -4 | 38 | 0 |
| 39 | Latvia | 56 | 39 | 28 | 46 | 29 | 33 | 40 | 53 | 32 | 59 | 47 | 54 | 45 | 6 | 40 | 1 |
| 40 | Brunei | 33 | 59 | 57 | 39 | 56 | 23 | 30 | 56 | 43 | 68 | 62 | 59 | 40 | 0 | 44 | 4 |
| 41 | Thailand | 50 | 51 | 20 | 65 | 39 | 37 | 43 | 20 | 57 | 14 | 36 | 40 | 28 | -13 | 39 | -2 |
| 42 | Slovakia | 69 | 45 | 21 | 41 | 53 | 55 | 58 | 31 | 31 | 44 | 41 | 50 | 49 | 7 | 42 | 0 |
| 43 | Russia | 54 | 34 | 49 | 66 | 25 | 52 | 39 | 66 | 39 | 5 | 50 | 37 | 33 | -10 | 46 | 3 |
| 44 | Greece | 61 | 26 | 72 | 24 | 18 | 59 | 66 | 76 | 35 | 43 | 46 | 58 | 66 | 22 | 47 | 3 |
| 45 | Hungary | 65 | 43 | 43 | 36 | 62 | 53 | 50 | 46 | 34 | 36 | 57 | 38 | 50 | 5 | 45 | 0 |
| 46 | Croatia | 67 | 33 | 39 | 26 | 45 | 45 | 64 | 59 | 37 | 52 | 65 | 67 | 58 | 12 | 48 | 2 |
| 47 | Montenegro | 48 | 48 | 62 | 33 | 50 | 34 | 49 | 54 | 46 | 75 | 63 | 61 | 60 | 13 | 50 | 3 |
| 48 | Georgia | 34 | 44 | 50 | 53 | 64 | 11 | 38 | 58 | 60 | 63 | 60 | 73 | 54 | 6 | 54 | 6 |
| 49 | Kazakhstan | 38 | 46 | 71 | 58 | 46 | 31 | 29 | 67 | 47 | 34 | 69 | 60 | 48 | -1 | 55 | 6 |
| 50 | Armenia | 44 | 58 | 47 | 50 | 59 | 17 | 41 | 57 | 59 | 70 | 44 | 56 | 57 | 7 | 51 | 1 |
| 51 | Indonesia | 36 | 49 | 38 | 70 | 60 | 41 | 60 | 27 | 67 | 8 | 31 | 31 | 31 | -20 | 43 | -8 |
| 52 | Bulgaria | 59 | 53 | 27 | 69 | 40 | 40 | 46 | 49 | 40 | 48 | 56 | 45 | 42 | -10 | 57 | 5 |
| 53 | Albania | 47 | 65 | 56 | 32 | 37 | 39 | 63 | 55 | 58 | 66 | 58 | 63 | 59 | 6 | 56 | 3 |
| 54 | Kuwait | 45 | 63 | 29 | 43 | 71 | 63 | 67 | 33 | 56 | 38 | 43 | 70 | 43 | -11 | 49 | -5 |
| 55 | Jordan | 46 | 61 | 55 | 49 | 52 | 51 | 70 | 39 | 50 | 54 | 42 | 42 | 53 | -2 | 60 | 5 |
| 56 | India | 29 | 50 | 45 | 72 | 61 | 73 | 55 | 32 | 71 | 2 | 28 | 28 | 35 | -21 | 41 | -15 |
| 57 | Romania | 57 | 60 | 31 | 54 | 57 | 48 | 56 | 70 | 48 | 30 | 70 | 66 | 55 | -2 | 61 | 4 |
| 58 | Serbia | 66 | 52 | 54 | 38 | 47 | 57 | 62 | 65 | 49 | 50 | 73 | 62 | 61 | 3 | 65 | 7 |
| 59 | Turkey | 52 | 47 | 53 | 74 | 30 | 44 | 73 | 43 | 55 | 11 | 51 | 53 | 44 | -15 | 52 | -7 |
| 60 | Bhutan | 27 | 71 | 65 | 62 | 70 | 67 | 21 | 35 | 66 | 76 | 53 | 64 | 64 | 4 | 53 | -7 |
| 61 | Vietnam | 55 | 62 | 46 | 55 | 69 | 72 | 37 | 48 | 63 | 21 | 64 | 55 | 46 | -15 | 64 | 3 |
| 62 | Lebanon | 76 | 74 | 74 | 34 | 49 | 54 | 72 | 37 | 36 | 53 | 37 | 46 | 75 | 13 | 58 | -4 |
| 63 | Iran | 60 | 35 | 66 | 47 | 41 | 75 | 76 | 71 | 61 | 18 | 59 | 51 | 56 | -7 | 62 | -1 |
| 64 | Sri Lanka | 53 | 56 | 59 | 48 | 65 | 66 | 75 | 38 | 70 | 46 | 45 | 48 | 65 | 1 | 59 | -5 |
| 65 | Tajikistan | 30 | 64 | 75 | 71 | 63 | 69 | 31 | 52 | 76 | 73 | 55 | 39 | 62 | -3 | 63 | -2 |
| 66 | Philippines | 71 | 73 | 36 | 68 | 54 | 76 | 53 | 29 | 62 | 23 | 52 | 52 | 47 | -19 | 66 | 0 |
| 67 | Ukraine | 73 | 54 | 76 | 64 | 26 | 65 | 57 | 74 | 64 | 35 | 66 | 47 | 63 | -4 | 68 | 1 |
| 68 | Mongolia | 68 | 68 | 60 | 59 | 48 | 46 | 47 | 73 | 65 | 65 | 72 | 68 | 72 | 4 | 72 | 4 |

| GMPC raking, i | Country | Institutions, α=1 | Infrastructure, α=2 | Macro-economic environment, α=3 | Health and primary education, α=4 | Higher education and training, α=5 | Goods market efficiency, α=6 | Labor market efficiency, α=7 | Financial market development, α=8 | Technological readiness, α=9 | Market size, α=10 | Business sophistication, α=11 | R&D innovation, α=12 | GCI rating (Eurasia) | Δ GCI rating | PC1 rating | Δ PC1 rating |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 69 | Bosnia-Herzegovina | 75 | 67 | 52 | 37 | 68 | 74 | 71 | 69 | 54 | 62 | 71 | 72 | 74 | 5 | 70 | 1 |
| 70 | Moldova | 74 | 57 | 73 | 60 | 66 | 60 | 61 | 75 | 52 | 72 | 75 | 76 | 68 | -2 | 69 | -1 |
| 71 | Laos | 49 | 69 | 69 | 75 | 72 | 58 | 25 | 51 | 72 | 64 | 61 | 57 | 70 | -1 | 67 | -4 |
| 72 | Kyrgyz Republic | 63 | 75 | 58 | 57 | 67 | 49 | 68 | 63 | 68 | 71 | 76 | 75 | 73 | 1 | 75 | 3 |
| 73 | Bangladesh | 70 | 70 | 64 | 56 | 74 | 61 | 69 | 60 | 73 | 29 | 68 | 71 | 71 | -2 | 74 | 1 |
| 74 | Cambodia | 72 | 72 | 63 | 73 | 76 | 71 | 33 | 62 | 69 | 57 | 67 | 69 | 69 | -5 | 73 | -1 |
| 75 | Nepal | 62 | 76 | 67 | 67 | 73 | 64 | 54 | 45 | 74 | 60 | 74 | 74 | 67 | -8 | 76 | 1 |
| 76 | Pakistan | 58 | 66 | 70 | 76 | 75 | 70 | 74 | 50 | 75 | 26 | 54 | 49 | 76 | 0 | 71 | -5 |

Source: Own elaboration and Global Competitiveness Report, 2017-2018.

### Fig. 1: GCI as compared to GMPC ranking




Source: Own elaboration and Global Competitiveness Report, 2017-2018.

## Conclusion

Measurement of the countries competitiveness is an ambiguous task not only because a competition is still a controversial term, but also for it takes into account a large number of indicators which are hard to compare.

We propose a kind of “natural” measure of national competitiveness as the sum of modified principal component scores weighted the shares of explained variance of original data. The typical features of this approach are twofold. Firstly, we do not impose any subjective weights to the factors that influence economic competitiveness as opposed, for instance, to GCI. Secondly, unlike ordinary PCA there is no neglect to any residual variance of original data. The generalized modified principal component analysis regards the overall data scatter.

The proposed methodology can be applied to construction of an overall economic indicator that reflects various qualitative aspects of national economic performance and can be treated as an alternative to GDP.

The further research can be devoted to application of this method of competitiveness assessment to calculations of economic effect of the Euroasian or other regional integration – at macro level of economic research and estimation of national companies success by evaluation of KPI or other indicators of economic activities - at micro level of research.

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