Alternative versions of the global competitive industrial performance ranking constructed by methods from social choice theory

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Alternative versions of the global competitive industrial performance ranking constructed by methods from social choice theory[1]

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Abstract: The Competitive Industrial Performance index (developed by experts of the UNIDO) is designed as a measure of national competitiveness. Index is an aggregate of eight observable variables, representing different dimensions of competitive industrial performance. Instead of using a cardinal aggregation function, what CIP's authors do, it is proposed to apply ordinal ranking methods borrowed from social choice: either direct ranking methods based on the majority relation (e.g. the Copeland rule, the Markovian method) or a multistage procedure of selection and exclusion of the best alternatives, as determined by a majority relation-based social choice solution concept (tournament solution), such as the uncovered set and the minimal externally stable set. The same method of binary comparisons based on the majority rule is used to analyse rank correlations. It is demonstrated that the ranking is robust but some of the new aggregate rankings represent the set of criteria better than the original ranking based on the CIP.

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1 Introduction

National competitiveness is broadly defined as an ability of a national economy to produce goods and services that meet the requirements set by international competition, while citizens enjoy a standard of living that is both improving and sustainable (Tyson, 1992). Although no general consensus on how to determine national competitiveness has been reached, it is agreed that this is not a self-contained concept. In order to measure it one has to define a set of factors such that their values either determine the level of national competitiveness or are determined by it. Once this set of factors has been defined, the measurement of national competitiveness becomes a problem of multiple criteria aggregation.

This paper deals with Competitive Industrial Performance Index (CIP), presented in UNIDO's Competitive Industrial Performance Report 2012/2013. The CIP Index is based on eight factors grouped into three sets called dimensions. Index value is a product of six values: two arithmetic means of two pairs of factors, which form the second dimension, and values of the other four factors. In this paper we do not question either definition of competitiveness, proposed by authors of the report, nor their choice of its observable correlates. We are interested in how the aggregation is performed.

The method of aggregation adopted by the authors of the CIP is theoretically problematic. Since the aggregation formula itself and the values of weights (factors for summations and powers for multiplication) are not unique, their choice have to be justified. It is extremely difficult if not altogether impossible to justify one's choices when the resulting variable is not directly observable and measurable. We have no such justification for the problem under consideration, therefore we cannot be sure that calculation of the CIP index presented in the report is a correct aggregation procedure yielding meaningful results. A *cardinal* value of this index will not tell us anything about performance of a given country if we do not compare it with other countries' values. The differences or proportions of index values across countries or over time have no evident interpretation as well. The only use we can make of the index is to order countries with respect to their CIP values in a given year.

As a partial solution to the problem of interpretation of cardinal values as well as another way to test the robustness of the ranking based on the CIP index we propose to apply *ordinal* ranking methods. We borrowed them from social choice theory since it is possible to frame any multi-criteria decision problem as a social choice problem. Eight industrial competitiveness factors are regarded as criteria. Countries are ranked by their values of each factor first, then eight factor-based-rankings are aggregated by the simple majority rule. The result of the aggregation is a binary relation. It tells us which country from a given pair is better than the other one with respect to majority of criteria. This majority relation is, generally, nontransitive. Therefore, in order to obtain a ranking we need to apply either a direct ranking method based on the majority relation (e.g. the Copeland rule) or a multistage procedure of selection and exclusion of the best countries, as determined by a majority relation-based social choice solution concept (tournament solution), such as the uncovered set and the minimal externally stable set.

The aims of the paper are the following. First, we use ordinal methods of aggregation to produce alternative versions of the CIP ranking. Then we employ rank correlation analysis in order to compare these new rankings and the original one to test the robustness of the CIP ranking.

The scheme of the research partially replicates that of our previous work on aggregate rankings of academic journals (Aleskerov et al., 2011, Aleskerov et al., 2013, Aleskerov et al., 2014).

The text is organized as follows. In Section 2 the original formula of the CIP Index is described. In Section 3 definitions are given for two majority relation-based ranking methods (the Copeland rule and Markovian method) and for three social choice solution concepts known as tournament solutions (the uncovered set, the minimal externally stable set, and the weak top cycle). The sorting procedure based on a tournament solution is formally described in this

Section. The values of correlation measures for both aggregate rankings and single-factor-based rankings are presented in Section 4. Section 5 contains formal comparison of rankings based on their correlation. Interpretation of the results and suggestions for further research are presented in Conclusion.

2 Competitive Industrial Performance Index

The Competitive Industrial Performance (CIP) index is a composite indicator proposed by experts of the United Nations Industrial Development Organization (UNIDO). It was first published in Industrial Development Report 2002/2003. Since then it has undergone two revisions.

The authors of the report define competitiveness as “the capacity of countries to increase their presence in international and domestic markets whilst developing industrial sectors and activities with higher value added and technological content dealing with international and domestic market shares and degree of industrialization” (UNIDO, 2013). In its present form, the CIP index is an aggregate of eight observable variables, which represent different aspects of industrial performance. The factors are grouped into three sets or dimensions:

Dimension I. Capacity to produce and export manufactures. It is measured by

1. MVApc – manufacturing value added per capita;
2. MXpc – manufactured exports per capita;

Dimension II. Technological deepening and upgrading. It is composed of

Subdimension IIa. Industrialization intensity. It is measured by

3. MHVAsh – medium- and high-tech manufacturing value added share in in total manufacturing value added;
4. MVAsh – manufacturing value added share in total GDP;

Subdimension IIb. Manufactured Exports Quality. It is measured by

5. MHXsh – medium- and high-tech manufactured exports share in total manufactured exports;
6. MXsh – manufactured exports share in total exports;

Dimension III. World impact. It is measured by

7. ImWMVA – impact of a country on world manufacturing value added, as measured by a country's share in world MVA;
8. ImWMT – impact of a country on world manufactures trade, as measured by a country's share in world manufactured exports.

Two pairs of indicators (MVApc, MXpc and MHXsh, MXsh) are aggregated into two larger indicators by taking their arithmetic mean. The resulting CIP Index value is a product of these six factors and can be written as follows:

$$CIP = MVApc \cdot MXpc \cdot \frac{MHVAsh + MVAsh}{2} \cdot \frac{MHXsh + MXsh}{2} \cdot ImWMWA \cdot ImWMT \qquad (1)$$

A ranking is an ordered set of positions occupied by alternatives compared (in our case – countries). A rank is a number of a position. A position in an ordering can be occupied by several countries, it is said then that such countries have coinciding ranks. Positions are ordered from 'best' to 'worst', with their ranks increasing. In the present paper we use data provided for the year 2010 in Competitive Industrial Performance Report 2012/2013 (UNIDO, 2013). First, countries are ranked in descending order by the values of each of eight basic indicators of UNIDO model. Then eight resulting rankings are aggregated into a single one. Countries' ranks in all rankings considered are presented in Table 6 in Appendix.

3 Aggregate rankings constructed by ordinal methods borrowed from social choice

Ranking of countries by values of a set of indicators is a multi-criteria evaluation problem. A common solution to a multi-criteria evaluation problem is to calculate a weighted sum of criteria values for each alternative and then rank alternatives by the value of the sum. As far as the order of alternatives is concerned, multiplying powers of criteria values is equivalent to weighted summation of their logarithms, weights being equal to powers. However, this approach has two fundamental deficiencies related to its *cardinal* nature. First, to obtain meaningful results one needs to be sure that it is theoretically possible and meaningful to perform the operation of summation and subtraction on the values of criteria or their logarithms in a given case since it is not, generally, possible. Second, the choice of weights (or powers) needs to be justified. Operations in formula (1) are mathematically correct, but their results are meaningless by themselves. Only their binary comparisons make sense. The choice of weights is based on the Laplace principle, evidently. Therefore we propose to apply purely *ordinal* ranking methods in order to test the robustness of the global ranking presented in UNIDO's report. We borrowed them from social choice theory since it is possible to frame any multi-criteria decision problem as a social choice problem (Arrow, Raynaud, 1986).

3.1 Basic notions

One of the main objectives of social choice theory is to determine what alternatives *will* be or *should* be chosen from all feasible alternatives on the basis of preferences that voters (i.e. individual participants in a collective decision-making process) have concerning these alternatives. It is possible to transfer social choice methods to a multi-criteria setting if one treats a ranking based on a certain criterion as a representation of preferences of a certain voter (or an expert). In our case, the set of rankings based on corresponding industrial performance factors is treated as a profile of preferences of eight virtual voters/experts.

Let A, $|A|=m$, $m\geq 3$, denote the general set of feasible alternatives; let N, $|N|=n$, $n\geq 2$ denote a group of experts making a collective decision by vote. A decision is a choice of certain alternatives from A. Preferences of a voter i, $i\in N$, with regard to alternatives from A are revealed through pairwise comparisons of alternatives and thus are modelled by a binary relation P_i on A, $P_i \subseteq A\times A$: if comparing an alternative x with an alternative y a voter i prefers x to y, then the ordered pair (x, y) belongs to the relation P_i, $(x, y) \in P_i$; it is also said that x dominates y with respect to P_i, xP_iy. If a voter is unable to compare two alternatives or believes they are of equal value, we will presume that he is indifferent regarding the choice between them, i.e. $(x, y)\notin P_i$ & $(y, x)\notin P_i$.

If chooser's preferences are known and a choice rule (a mapping of the set of binary relations on A onto the set of nonempty subsets of A) is given, then it is possible to determine what alternatives should be the result of his choice. Thus the social choice problem can be solved if one: 1) knows individual preferences, 2) defines a binary relation μ, $\mu\subseteq A\times A$ that models collective preferences (i.e. collective opinion with regard to alternatives from A), and 3) determines a choice rule $S(\mu, A)$: $\{\mu\}\rightarrow 2^A\setminus\varnothing$, also called a solution. Probably the most popular method to construct μ from individual preferences is to apply the majority rule. In this case, μ is called a majority (preference) relation: x dominates y via μ if the number of voters who prefer x to y is greater than the number of those who prefer y to x, $x\mu y\Leftrightarrow|N_1|>|N_2|$, where $N_1=\{i\in N|\ xP_iy\}$, $N_2=\{i\in N|\ yP_ix\}$.

The choice of this particular rule of aggregation is prescribed by the social choice theory since the majority rule, and this rule only, satisfies several important normative conditions (see Aizerman, Aleskerov, 1983), such as independence of irrelevant alternatives, Pareto-efficiency, neutrality (equal treatment of alternatives), and anonymity (equal treatment of voters), which hold in our case as well. Moreover, in a multi-criteria setting the application of this rule allows one to obtain aggregated evaluations of alternatives without recourse to arithmetic operations on criteria, and consequently removes the problem of their theoretical justification.

We would like to test the robustness of the model with respect to change of aggregation method. Therefore we will choose weights on the basis of the principle of equal treatment of factors. In the original formula six factors are treated as being of equal importance since they have the same power. Four of this factors (MVApc, MXpc, ImWMVA and ImWMT) are independent indicators. Therefore we should presume they must have the same weight. Two of this factors are arithmetic means of another two indicators, consequently all indicators, which are grouped in pairs (i.e. MVApc, MXpc and MHXsh, MXsh), are supposed to be of the same importance. Since pairs of these indicators are equal in importance with other four factors, we have to assume that the authors of the CIP index suppose that any unpaired indicator is twice as important as any paired one. We reflect this difference in importance by giving 1 vote to a virtual voter representing a paired indicator and 2 votes to a voter representing an unpaired one.

It follows from the definition that any μ is asymmetric, $(x, y)\in\mu \Rightarrow (y, x)\notin\mu$. If the following holds $x\neq y \wedge (x, y)\notin\mu \wedge (y, x)\notin\mu$, then alternatives x and y are tied, and both ordered pairs belong to a set of ties τ, $\tau\subseteq A\times A$, $(x, y)\in\tau$ & $(y, x)\in\tau$. It is evident that a set of ties τ is an irreflexive and symmetric binary relation.

For computational purposes a majority relation μ is represented by a majority matrix $\mathbf{M}=[m_{xy}]$, defined in the following way:

$$m_{xy}=1 \Leftrightarrow (x, y)\in\mu \text{ or } m_{xy}=0 \Leftrightarrow (x, y)\notin\mu.$$

A matrix $\mathbf{T}=[t_{ij}]$ representing a set of ties τ is defined in the same way.

To define several choice rules we will also need the notions of the lower section, the upper section and the horizon of the alternative x. The lower section of an alternative x is the set $L(x)$ of all alternatives dominated by x via μ, $L(\mathrm{x})=\{y|\ x\mu y\}$, the upper section of x is the set $D(x)$ of all alternatives that dominate x via μ, $D(x)=\{y|\ y\mu x\}$, the horizon of x is the set $H(x)$ of all alternatives that tie x, $H(x)=\{y|\ y\tau x\}$.

3.2 The Copeland rule

A majority relation quite often happens not to be a ranking itself since it is generally nontransitive. That is, a majority relation often contains cycles. For instance, there are often alternatives x, y and z such that $x\mu y$ and $y\mu z$ and $z\mu x$ (a 3-step μ-cycle: x is majority preferred to y, which is majority preferred to z, which is majority preferred to x). This result is known as the

Condorcet paradox. In order to check if majority relation in our case is transitive or not and to evaluate how nontransitive it is, we calculate the number of 3-step μ-cycles, 4-step μ-cycles and 5-step μ-cycles for our set of countries. This can be done by raising a majority matrix $\mathbf{M}$ to the power of 3, 4 and 5, correspondingly. When k equals 3, 4 or 5, the number of k-step μ-cycles q_k is equal to the trace (the sum of all diagonal entries) of the matrix $\mathbf{M}^k$ divided by k: $q_k = \frac{\mathrm{tr}(\mathbf{M}^k)}{k}$ (Cartwright, Gleason, 1966). Numbers of cycles for each k are given in Table 1.

Table 1. Numbers of 3-, 4- and 5-step cycles in μ

	Number of cycles
3-step cycles	638
4-step cycles	5928
5-step cycles	52754

As we see, the Condorcet paradox occurs in our case. In order to bypass the nontransitivity problem, several ranking methods have been proposed. Probably the simplest one is the Copeland rule (Copeland, 1951). The idea of this method is the following: the greater the number of alternatives that are worse than a given one, the better this alternative is; and it is determined through pairwise comparisons (based on a majority relation) whether a given alternative is either better or worse than another one. Alternatively, it could be put that an alternative is good if the number of alternatives that are better is small. Finally, one can combine these two principles.

Formally, the Copeland aggregate ranking is an ordering of the alternatives by their score $s(x)$ (called the Copeland score), as given by one of the following formulae:

Version 1. $s_1(x)=|L(x)|-|D(x)|$

Version 2. $s_2(x)=|L(x)|$

Version 3. $s_3(x)=|A|-|D(x)|$

All three versions yield the same result when there are no ties. Vectors $\mathbf{s}_1$, $\mathbf{s}_2$ and $\mathbf{s}_3$ of scores, which are attributed to countries according to these versions, are computed by the formulae: $\mathbf{s}_2=\mathbf{M}\cdot\mathbf{a}$, $\mathbf{s}_3=(\mathbf{I}-\mathbf{M}^{tr})\cdot\mathbf{a}$, $\mathbf{s}_1= \mathbf{s}_2 + \mathbf{s}_3 - m\cdot\mathbf{a}$, where $\mathbf{I}$ and $\mathbf{a}$ denote, correspondingly, the matrix and the vector, which entries and components are all equal to 1.

Example 1. Let us consider how the second version of the Copeland rule ranks countries in the following example. Let us assume that there are m=5 countries, $A=\{x_1, x_2, x_3, x_4, x_5\}$, and n=3 factors generating three rankings. Let countries be ordered $x_1>x_2>x_3>x_4>x_5$ by the 1st factor, $x_4>x_5>x_2>x_3>x_1$ by the 2nd factor, $x_5>x_3>x_1>x_2>x_4$ by the 3d factor. The majority matrix **M** and the Copeland score (cardinality of the lower section) of a given country are presented in Table 2.

Table 2. Majority matrix and the Copland score in Example 1

Majority matrix **M**						Cardinality of the lower section $\|L(x)\|$
	x_1	x_2	x_3	x_4	x_5	
x_1	0	1	0	1	0	2
x_2	0	0	1	1	0	2
x_3	1	0	0	1	0	2
x_4	0	0	0	0	1	1
x_5	1	1	1	0	0	3

According to the second version of the Copeland rule, the aggregate ranking contains three ranks: 1) x_5; 2) x_1 - x_2 - x_3; 3) x_4.

3.3 A sorting procedure based on tournament solutions

In order to construct a ranking, we can also use solutions to the problem of optimal social choice. Let us consider the following iterative procedure. A solution concept $S(\mu, A)$ is a choice correspondence that determines a set $B_{(1)}$ of those alternatives from a set A that are considered to be the best with respect to collective preferences expressed in a form of a majority relation μ: $B_{(1)}=S(\mu, A)$. Alternatives from $B_{(1)}$ are of 'prime quality' choices comparing with all other alternatives. Let us exclude them and repeat the sorting procedure for the set $A\backslash B_{(1)}$. Then a set $B_{(2)}=S(\mu, A\backslash B_{(1)})=S(\mu, A\backslash S(\mu, A))$ will be determined. This set contains second best choices – they are worse than alternatives from $B_{(1)}$ and better than options from $A\backslash(B_{(1)}\cup B_{(2)})$. After a finite number of selections and exclusions, all alternatives from A will be separated by classes $B_{(k)}=S(\mu, A\backslash(B_{(k-1)}\cup B_{(k-2)}\cup...\cup B_{(2)}\cup B_{(1)}))$ according to their 'quality', and these classes define the ranking we are looking for.

In this study, we use two tournament solutions: the uncovered set and the externally stable set. The first solution is based on the following idea: let us make the notion of majority preferences stronger, so it becomes always possible to choose undominated alternatives[4]. That is, when the set of undominated alternatives of μ is empty, let us select undominated alternatives of a special subset α of μ, $\alpha \subseteq \mu$. The subrelation α is defined in the following way. It is said that an alternative x covers y, $x\alpha y$, if x μ-dominates both y and all alternatives, which are μ-dominated by y: $x\alpha y \Leftrightarrow (x\mu y \wedge \forall z \in A\ (y\mu z \Rightarrow x\mu z))$ (Miller, 1980). That is, the majority of voters strongly prefer x to y when 1) they prefer x to y, and 2) there is no alternative z, such that it is strictly less preferable than y and at least as preferable as x. The best alternatives are those not covered (not dominated with respect to α) by any other alternatives. Their set is called the uncovered set[5] *UC*. The uncovered set is always nonempty due to the transitivity of the covering relation α.

Instead of choosing 'strong' candidates as is the case with the uncovered set, it is possible to choose candidates from a 'strong' group. The second solution is based on this idea of choosing from a set endowed with some 'good' properties. A set *ES* is externally stable if for any alternative x outside *ES* there exists an alternative y in *ES* that is more preferable for the majority of voters than x: $\forall x \notin ES\ \exists y\colon y \in ES \wedge y\mu x$ (von Neumann, Morgenstern, 1944). An externally stable set is minimal if none of its proper subsets is externally stable. An alternative is optimal if it belongs to at least one minimal externally stable set *MES*, therefore the tournament solution is the union of all such sets, which is likewise denoted as *MES* (Subochev, 2008; see also, Aleskerov, Subochev, 2013)[6]. *MES* is always nonempty.

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[4] Due to the Condorcet paradox, the set of alternatives undominated via the majority relation itself (the so-called core) may (and almost always will) be empty.

[5] There exist alternative definitions of the covering relation and, consequently, of the uncovered set. They are listed in Aleskerov, Subochev (2013).

[6] Minimal externally stable set was introduced in Subochev (2008) as a version of another tournament solution – minimal weakly stable set (MWS) introduced in Aleskerov and Kurbanov (1999). Therefore in Subochev (2008) and in Aleskerov, Subochev (2009) this solution concept is called the second version of the minimal weakly stable set

When *UC* (or *MES*) is determined for the initial set of countries, the countries comprised by this set receive the first (best) rank. After that, these countries are excluded from the general set *A* and the procedure repeats iteratively, as it was explained in the beginning of this section.

The uncovered set and the union of minimal externally stable sets can be calculated through their matrix-vector representations given in Aleskerov, Subochev (2009; 2013). These representations use the matrices **M** and **T** defined in Subsection 3.1.

3.4 The Markovian method

Finally, we would like to apply a version of a ranking called the Markovian method, since it is based on an analysis of Markov chains that model stochastic moves from vertex to vertex via arcs of a digraph representing a binary relation μ. The earliest versions of this method were proposed by Daniels (1969) and Ushakov (1971). References to other papers can be found in Chebotarev, Shamis (1999).

To explain the method let us consider its application in the following situation. Suppose alternatives from *A* are chess-players. Only two persons can sit at a chess-board, therefore in making judgments about players' relative strength, we are compelled to rely upon results of binary comparisons, i.e. separate games. Our aim is to rank players according to their strength. Since it is not possible with a single game, we organize a tournament.

Before the tournament starts we separate patently stronger players from the weaker ones by assigning each player to a certain league, a subgroup of players who are relatively equal in their strength. To make the assignments, we use the sorting procedure described in the previous subsection. The tournament solution that is used for the selection of the strongest players is the weak top cycle *WTC* (Ward, 1961; Schwartz, 1970, 1972, 1977; Good, 1971; Smith, 1973). It is

and is denoted as MWS^{II}. The version of the uncovered set we use here is denoted as UC^{II} in the aforementioned texts.

defined in the following way. A set *WTC* is called the weak top cycle if 1) any alternative in *WTC* μ-dominates any alternative outside *WTC*: $\forall\ x \notin WTC,\ y \in WTC \Rightarrow y \mu x$, and 2) none of its proper subsets satisfies this property.

The relative strength of players assigned to different leagues is determined by a binary relation μ, therefore in order to rank all players all we need to know is how to rank players of the same league. Each league receives a chess-board. Since there is only one chess-board per league, the games of a league form a sequence in time.

Players who participate in a game are chosen in the following way: a player who has been declared a (current) winner in the previous game remains at the board, her rival is randomly chosen from the rest of the players, among whom the loser of the previous game is also present. In a given league, all probabilities of being chosen are equal. If a game ends in a draw, the previous winner, nevertheless, loses her title and it passes to her rival. Therefore, despite ties being allowed, there is a single winner in each game. It is evident that the strength of a player can be measured by counting a relative number of games, in which he has been declared a winner (i.e. the number of his wins divided by the total number of games in a tournament).

In order to start a tournament we need to decide who is declared a winner in a fictitious 'zero-game'. However, the longer a tournament goes (i.e. the greater the number of tournament games is), the smaller is the influence of this decision on the relative number of wins of any player. In the limit when the number of games tends to infinity relative numbers of wins are completely independent of who had been given 'the crown' before the tournament started.

Instead of calculating the limit of the relative number of wins, one can find the limit of the probability a player will be declared a winner in the last game of the tournament since these values are equal. We can count the probability and its limit using matrices **M** and **T** defined above.

Suppose we somehow know the relative strength of players in each pair of them. Also, suppose this strength is constant over time and is represented by binary relations μ and τ.

Therefore, if we know μ and the names of the players who are sitting at the chess-board, we can predict the result of the game: the victory of x (if $x\mu y$), the victory of y (if $y\mu x$) or a draw (if $x\tau y$).

Let $\mathbf{p}^{(k)}$ denote a vector, i-th component $p_i^{(k)}$ of which is the probability a player number i is declared the winner of a game number k. Two mutually exclusive situations are possible. The first case – the player number i is declared the winner in both the previous game (game number k-1) and the current game. She can be declared the winner in the game number k if and only if her rival (who has been chosen by lot) belongs to the lower section of i. The probability that the i-th player was declared the winner in the game number k-1 is $p_i^{(k-1)}$, the probability of her rival being in $L(i)$ equals $\frac{s_2(i)}{m-1}$, where $s_2(i)$ is the Copeland score (the 2nd version), $s_2(x)=|L(x)|$. Thus, the probability of the i-th player being declared the winner in game number k is $p_i^{(k-1)} \cdot \frac{s_2(i)}{m-1}$.

The second case – the player number i is declared the winner in the current game, but not in the previous one. He can be declared the winner in game number k if and only if 1) he has been chosen by lot as a rival to the winner in the game number k-1, the probability of which equals $\frac{1}{m-1}$; and 2) if the (k-1)-th winner is in the lower section or in the horizon of the i-th player, a probability of which equals $\sum_{j=1}^{m}(m_{ij}+t_{ij}) \cdot p_j^{(k-1)}$.[7] Thus the probability $p_i^{(k)}$ can be determined from the following equation:

$$p_i^{(k)} = p_i^{(k-1)} \cdot \frac{s_2(i)}{m-1} + \frac{1}{m-1} \cdot \sum_{j=1}^{m}(m_{ij}+t_{ij}) \cdot p_j^{(k-1)} \tag{2}$$

Formula (2) can be rewritten in a matrix-vector form as:

$$\mathbf{p}^{(k)} = \mathbf{W} \cdot \mathbf{p}^{(k-1)} = \frac{1}{m-1} \cdot (\mathbf{M}+\mathbf{T}+\mathbf{S}) \cdot \mathbf{p}^{(k-1)} \tag{3}$$

The matrix $\mathbf{S}=[s_{ij}]$ is defined as $s_{ii}=s_2(i)$ and $s_{ij}=0$ when $i\neq j$.

Consequently, passing the title of the current winner from player to player is a Markovian process with the transition matrix $\mathbf{W}$.

We are interested in the vector $\mathbf{p}=\lim_{k\to\infty} \mathbf{p}^{(k)}$. It is not hard to prove that no matter what

[7] Here notations m, m_{ij}, t_{ij} are those introduced in Subsection 3.1.

the initial conditions are (i.e. what the value of $\mathbf{p}^{(0)}$ is), the limit vector is an eigenvector of the matrix **W** corresponding to the eigenvalue λ=1 (see, for instance, Laslier (1997)). Therefore **p** is determined by solving the system of linear equations $\mathbf{W}\cdot\mathbf{p}=\mathbf{p}$. To rank players in a league, one needs to order them by decreasing values of p_i. Since we have pre-sorted players using *WTC*, none of the components p_i is equal to zero (Laslier, 1997).

Ranks of the countries in the six aggregate rankings are given in Table 6 in Appendix.

4 Correlations

The number of the alternative's position in a ranking is a rank variable. Therefore, to evaluate the (in)consistency of two rankings, one needs to apply ranking measures of correlation. We use two related but not identical measures based on the Kendall distance: the Kendall rank correlation index τ_b (Kendall, 1938) and the share of coinciding pairs r.

To remind the reader what the Kendall distance is, let us consider a pair of countries and compare their positions in two rankings. If a country is placed above the second one in the first ranking, but at the same time it is placed below the other one in the second ranking, then this pair of countries counts as an inversion. The Kendall distance between two rankings is the number of inversions N_- (a number of unordered pairs of objects ranked inversely in two ranking). Correspondingly, the greater the number of inversions is, the farther apart (i.e. the more disparate) the rankings are. The Kendall rank correlation coefficient τ_b depends on the Kendall distance in the following way:

$$\tau_b=\frac{N_+-N_-}{\sqrt{(N-n_1)\cdot(N-n_2)}} \tag{3}$$

Here N_+ is the number of coinciding pairs, which are not ties, i.e. such country pairs, where one country is placed above the second one in both rankings; n_1 is the number of pairs, where both countries have the same rank in the first ranking; n_2, correspondingly, is the number of pairs, where both countries have the same rank in the second ranking. Obviously, $N_+ + N_- = N - n_1 - n_2 + N_0$, where N_0 is the number of pairs tied in both rankings.

The share of coinciding pairs r is a percentage of pairs ranked in the same way in both rankings, $r = 100 \cdot \frac{N_+ + N_0}{N}$. This measure has a simple probabilistic interpretation. If we know that alternative x is ranked above alternative y in ranking R_1 and guess that in ranking R_2 they are placed in the same order, then r is the probability that our prediction is correct. When r=50%, probability of being right equals probability of being wrong, which means two rankings do not correlate.

The main difference between τ_b and r is that the latter 'punishes' rankings containing too many ties, while the former does not. Values of τ_b and r for the eight factor-based and aggregate rankings are given in Table 3.

Table 3. Values of correlation measures

	MVApc	MXpc	MHVAsh	MVAsh	MHXsh	MXsh	ImWMVA	ImWMT	the CIP index	Copeland (1)	Copeland (2)	Copeland (3)	*UC*	*MES*	Markovian
Kendall's τ_b															
MVApc	1,000	0,767	0,476	0,318	0,465	0,365	0,510	0,553	0,715	0,718	0,715	0,723	0,714	0,691	0,714
MXpc	0,767	1,000	0,487	0,289	0,466	0,421	0,440	0,576	0,704	0,716	0,716	0,716	0,706	0,689	0,709
MHVAsh	0,476	0,487	1,000	0,319	0,471	0,399	0,517	0,578	0,595	0,637	0,633	0,643	0,654	0,635	0,633
MVAsh	0,318	0,289	0,319	1,000	0,319	0,381	0,436	0,422	0,440	0,456	0,455	0,458	0,471	0,476	0,448
MHXsh	0,465	0,466	0,471	0,319	1,000	0,354	0,422	0,470	0,529	0,559	0,563	0,556	0,576	0,571	0,556
MXsh	0,365	0,421	0,399	0,381	0,354	1,000	0,289	0,370	0,430	0,476	0,472	0,482	0,492	0,472	0,485
ImWMVA	0,510	0,440	0,517	0,436	0,422	0,289	1,000	0,808	0,732	0,701	0,703	0,701	0,717	0,720	0,679
ImWMT	0,553	0,576	0,578	0,422	0,470	0,370	0,808	1,000	0,833	0,801	0,805	0,798	0,808	0,801	0,774
CIP	0,715	0,704	0,595	0,440	0,529	0,430	0,732	0,833	1,000	0,930	0,926	0,925	0,907	0,877	0,888
Cop. (1)	0,718	0,716	0,637	0,456	0,559	0,476	0,701	0,801	0,930	1,000	0,979	0,982	0,937	0,897	0,921
Cop. (2)	0,715	0,716	0,633	0,455	0,563	0,472	0,703	0,805	0,926	0,979	1,000	0,959	0,936	0,899	0,905
Cop. (3)	0,723	0,716	0,643	0,458	0,556	0,482	0,701	0,798	0,925	0,982	0,959	1,000	0,935	0,896	0,933
UC	0,714	0,706	0,654	0,471	0,576	0,492	0,717	0,808	0,907	0,937	0,936	0,935	1,000	0,915	0,913
MES	0,691	0,689	0,635	0,476	0,571	0,472	0,720	0,801	0,877	0,897	0,899	0,896	0,915	1,000	0,878
Markovian	0,714	0,709	0,633	0,448	0,556	0,485	0,679	0,774	0,888	0,921	0,905	0,933	0,913	0,878	1,000
Percentage of coinciding pairs (*r*)															
MVApc	100	88,36	73,80	65,89	73,27	68,24	74,89	77,13	85,66	85,77	85,32	85,59	81,77	78,78	85,72
MXpc	88,36	100	74,32	64,46	73,30	71,02	71,43	78,25	85,11	85,65	85,34	85,23	81,38	78,70	85,44
MHVAsh	73,80	74,32	100	65,91	73,55	69,93	75,23	78,33	79,65	81,68	81,22	81,57	78,84	76,10	81,65
MVAsh	65,89	64,46	65,91	100	65,96	69,02	71,23	70,55	71,92	72,67	72,33	72,40	69,96	68,49	72,37
MHXsh	73,27	73,30	73,55	65,96	100	67,68	70,53	72,98	76,36	77,82	77,73	77,27	75,10	73,03	77,80
MXsh	68,24	71,02	69,93	69,02	67,68	100	63,89	68,00	71,42	73,63	73,19	73,60	71,01	68,33	74,24
ImWMVA	74,89	71,43	75,23	71,23	70,53	63,89	100	89,46	85,86	84,28	84,08	83,89	81,49	79,73	83,34
ImWMT	77,13	78,25	78,33	70,55	72,98	68,00	89,46	100	90,98	89,29	89,22	88,77	85,97	83,62	88,13
CIP	85,66	85,11	79,65	71,92	76,36	71,42	85,86	90,98	100	96,24	95,75	95,56	91,14	87,68	94,34

Cop. (1)	85,77	85,65	81,68	72,67	77,82	73,63	84,28	89,29	96,24	100	98,40	98,40	92,65	88,66	95,91
Cop. (2)	85,32	85,34	81,22	72,33	77,73	73,19	84,08	89,22	95,75	98,40	100	96,95	92,59	88,68	94,80
Cop. (3)	85,59	85,23	81,57	72,40	77,27	73,60	83,89	88,77	95,56	98,40	96,95	100	92,38	88,62	96,06
UC	81,77	81,38	78,84	69,96	75,10	71,01	81,49	85,97	91,14	92,65	92,59	92,38	100	89,08	91,45
MES	78,78	78,70	76,10	68,49	73,03	68,33	79,73	83,62	87,68	88,66	88,68	88,62	89,08	100	87,72
Markovian	85,72	85,44	81,65	72,37	77,80	74,24	83,34	88,13	94,34	95,91	94,80	96,06	91,45	87,72	100

All eight basic single-indicator-based rankings correlate positively with respect to both measures (τ_b>0; *r*>50%). Their correlation is moderately strong (τ_b>0,3; *r*>65%) in most cases. It is very strong (τ_b>0,75; *r*>85%) in two cases: {ImWMT, ImWMVA}, {MVApc, MXpc}. This is because national manufacturing value added and manufactured exports correlate strongly.

Direct observations of values in Tables 3 also confirm natural expectations: all aggregate rankings, both old one and new ones, are better correlated with the set of eight single-indicator-based rankings than the latter with each other.

Original CIP ranking correlate strongly and positively with all new aggregate rankings, the lowest level of contradictions being 3,76% (with the 1st version of the Copeland rule), the highest – 12,32% (with the ranking based on *MES*). The pair {CIP, *MES*} demonstrated the lowest correlation among all pairs of all aggregate rankings according to both measures. Therefore we can use values of τ_b and *r* for this pair in order to evaluate robustness of CIP. We may conclude that strong (τ_b>0,75; *r*>85%) correlation of these two ranking support the claim that the CIP ranking is robust.

One can observe that values of *r* for pairs of aggregate rankings vary greater than their values of τ_b. This difference between two measures can be explained as follows: the scales of rankings produced by sorting contain too few grades as compared to scales of other rankings, consequently rankings based on *UC* and *MES* contain significantly more ties than other rankings. As a result, values of *r* for pairs containing either of this two rankings are lower, since this measure (unlike τ_b) ‘punishes’ rankings containing too many ties: being a tie in a ranking based on *UC* or *MES*, a pair most probably will not be a tie in another ranking and so it will not contribute to the numerator of *r*, while *r*’s denominator remains constant across all pairs.

5 Formal comparison of rankings

Let us employ the same method of binary multi-criteria comparisons to analyze rankings more formally. The problem of aggregation can be reformulated as a choice of a single object representing a given group of objects. In our case we need to choose a ranking that will represent the set of eight single-indicator-based rankings $\{P_i\}$, i=1÷8. We have fifteen candidates: seven aggregate rankings and eight initial rankings. Let us use the same idea of binary multi-criteria comparisons and majority relation in order to determine the best representations.

Let us say that ranking R_1 represents single-indicator-based ranking P_i better than ranking R_2 does if R_1 is better correlated with P_i than R_2. If P_i represents preferences of voter i then we may suppose that R_1 represents i's preferences better than R_2 does, so voter i will most likely vote for R_1 against R_2, when they are compared. Then R_1 should be considered a better representative for the set of rankings $\{P_i\}$ than R_2 if R_1 is better correlated with (is closer to) a (weighted) majority of rankings from this set than R_2 is. Let us remind the reader that weight v_i (the number of votes that voter i has) reflects relative importance attributed to the corresponding aggregated variable i. In our case, the vector of weights/votes is **v**=(2, 2, 1, 1, 1, 1, 2, 2).

Each ranking R is characterized by 8-component vector $\mathbf{c}(R)$, its i-th component being the value of a given correlation measure for this ranking and corresponding single-indicator-based ranking P_i: either $c_i(R) = \tau_b(R, P_i)$ or $c_i(R) = r(R, P_i)$. We perform binary comparisons of vectors $\mathbf{c}(R)$ and define a majority relation on the set of twelve rankings in the following way: $R_1\ \mu\ R_2 \Leftrightarrow V_1>V_2$, where $V_1=\sum_{\{i|c_i(R_1)>c_i(R_2)\}} v_i$, $V_2=\sum_{\{i|c_i(R_2)>c_i(R_1)\}} v_i$.

Table 4 contains results of binary comparisons based on measures τ_b and r. The first number in a cell equals 1 if the ranking of the row correlates with eight single-factor rankings better than the ranking of the column with respect to a given measure of correlation. It equals 0 otherwise, that is the first numbers are majority matrices' entries. The second number (in brackets) is a number of those initial rankings that are closer to the ranking of the row than to the ranking of the column with respect to a given measure of correlation.

Table 4. Binary comparisons of rankings (majority matrices and numbers of 'wins')

	MVApc	MXpc	MHVAsh	MVAsh	MHXsh	MXsh	ImWMVA	ImWMT	the CIP index	Copeland (1)	Copeland (2)	Copeland (3)	*UC*	*MES*	Markovian
Kendall's τ_b															
MVApc	0(0)	1(11)	1(10)	1(10)	1(8)	1(7)	0(5)	0(3)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)
MXpc	0(1)	0(0)	0(4)	0(5)	0(2)	0(1)	0(2)	0(2)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)
MHVAsh	0(2)	1(8)	0(0)	1(10)	0(2)	0(2)	0(4)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)
MVAsh	0(2)	1(7)	0(2)	0(0)	0(2)	0(2)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)
MHXsh	0(4)	1(10)	1(10)	1(10)	0(0)	0(5)	0(6)	0(4)	0(4)	0(4)	0(4)	0(4)	0(4)	0(4)	0(4)
MXsh	0(5)	1(11)	1(10)	1(10)	1(7)	0(0)	0(6)	0(5)	0(4)	0(4)	0(4)	0(4)	0(4)	0(4)	0(4)
ImWMVA	1(7)	1(10)	1(8)	1(11)	0(6)	0(6)	0(0)	0(3)	0(2)	0(4)	0(4)	0(4)	0(4)	0(4)	0(4)
ImWMT	1(9)	1(10)	1(11)	1(11)	1(8)	1(7)	1(9)	0(0)	0(4)	0(4)	0(4)	0(4)	0(4)	0(4)	0(4)
CIP	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(10)	1(8)	0(0)	0(4)	0(4)	0(4)	0(6)	1(8)	0(6)
Cop. (1)	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	1(8)	0(0)	1(7)	1(7)	0(4)	0(6)	1(11)
Cop. (2)	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	1(8)	0(5)	0(0)	0(5)	0(4)	0(6)	1(10)
Cop. (3)	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	1(8)	0(5)	1(7)	0(0)	0(4)	0(6)	1(10)
UC	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	0(6)	1(8)	1(8)	1(8)	0(0)	1(9)	1(8)
MES	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	0(4)	0(6)	0(6)	0(6)	0(3)	0(0)	1(7)
Markovian	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	0(6)	0(1)	0(2)	0(2)	0(4)	0(5)	0(0)
Percentage of coinciding pairs (*r*)															
MVApc	0(0)	1(11)	1(10)	1(10)	1(8)	1(7)	0(5)	0(3)	0(1)	0(1)	0(1)	0(1)	0(1)	0(3)	0(1)
MXpc	0(1)	0(0)	0(4)	0(5)	0(2)	0(1)	0(2)	0(2)	0(1)	0(1)	0(1)	0(1)	0(1)	0(2)	0(1)
MHVAsh	0(2)	1(8)	0(0)	1(10)	0(2)	0(2)	0(4)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)
MVAsh	0(2)	1(7)	0(2)	0(0)	0(2)	0(2)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(1)	0(2)	0(1)
MHXsh	0(4)	1(10)	1(10)	1(10)	0(0)	0(5)	0(6)	0(6)	0(4)	0(4)	0(4)	0(4)	0(4)	0(5)	0(4)
MXsh	0(5)	1(11)	1(10)	1(10)	1(7)	0(0)	0(6)	0(6)	0(4)	0(4)	0(4)	0(4)	0(5)	0(6)	0(4)
ImWMVA	1(7)	1(10)	1(8)	1(11)	0(6)	0(6)	0(0)	0(3)	0(2)	0(4)	0(4)	0(4)	0(5)	0(5)	0(4)
ImWMT	1(9)	1(10)	1(11)	1(11)	0(6)	0(6)	1(9)	0(0)	0(4)	0(4)	0(4)	0(4)	0(5)	0(6)	0(4)
CIP	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(10)	1(8)	0(0)	0(4)	0(6)	0(6)	1(12)	1(12)	0(4)
Cop. (1)	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	1(8)	0(0)	1(12)	1(12)	1(12)	1(12)	1(11)
Cop. (2)	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	0(6)	0(0)	0(0)	1(7)	1(12)	1(12)	0(4)
Cop. (3)	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	0(6)	0(0)	0(5)	0(0)	1(12)	1(12)	0(5)
UC	1(11)	1(11)	1(11)	1(11)	1(8)	1(7)	1(7)	1(7)	0(0)	0(0)	0(0)	0(0)	0(0)	1(12)	0(0)
MES	1(9)	1(10)	1(11)	1(10)	1(7)	0(6)	1(7)	0(6)	0(0)	0(0)	0(0)	0(0)	0(0)	0(0)	0(0)
Markovian	1(11)	1(11)	1(11)	1(11)	1(8)	1(8)	1(8)	1(8)	1(8)	0(1)	1(8)	1(7)	1(12)	1(12)	0(0)

A binary relation (or its matrix) can be represented by a digraph. Vertices represent alternatives, arcs (links with arrows) represent ordered pairs: the alternative, which is represented by arc's starting point, dominates (via relation represented by the digraph) the alternative, which is represented by arc's ending point. Digraphs representing matrices in Table 4 are depicted on Figure 1. By convention, if a pair of vertices is not connected it means that the arc begins at the higher vertex and goes down. A dashed line without arrow indicates a tie.

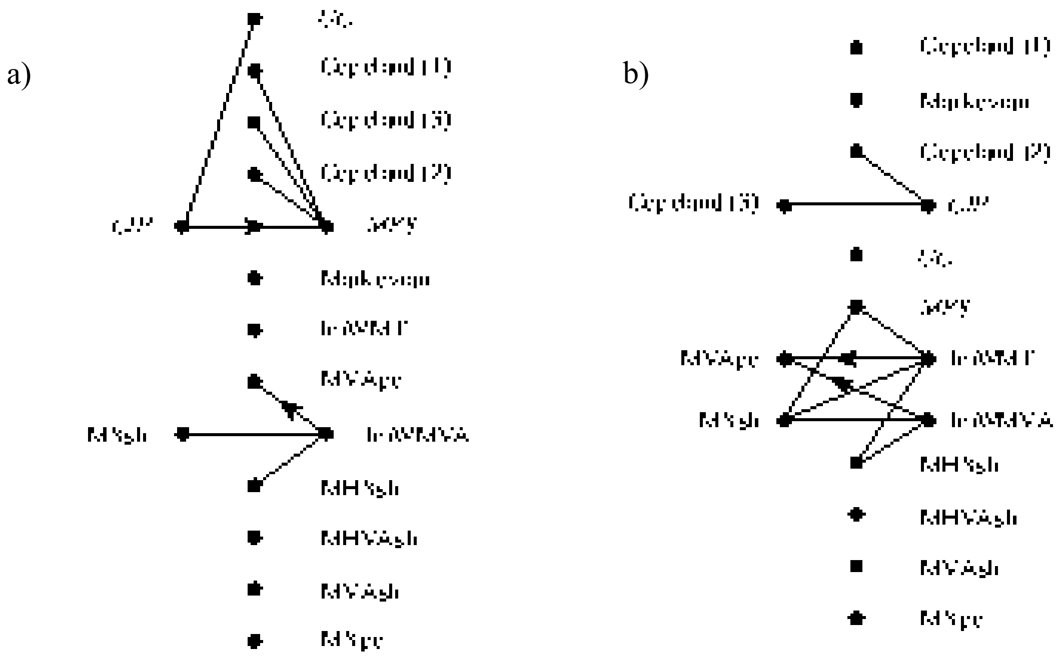

Figure 1. Ordering of rankings according to τ_b (a) and *r* (b).

In both cases μ is a strict partial order but not a weak order and, consequently it is not a ranking itself. We need again somehow to 'mend' nontransitive μ in order to get a ranking. First, one may note that in both cases μ is very close (with respect to the Kendal distance) to a linear order (i.e. a ranking discriminating all alternatives). Therefore we can represent μ by a closest linear order. In the first case, when ranking are compared by τ_b, the linear order at a minimal distance from μ is unique. In the second case, there are six closest linear orders, which differ only with respect to how they order the triplet {Copeland 2, Copeland 3, CIP} and the pair {*MES*, ImWMT}. In both cases the Kendall distance from μ to closest linear orders equals 0 (i.e.

there are no inversions). We may unite six linear orders in a weak order by assigning rank 3 to all alternatives from the triplet and rank 5 to *MES* and ImWMT. Final rankings of ranking are presented in Table 5.

Table 5. Two rankings of rankings

Rank	**Ordered by**	
	$\boldsymbol{\tau_b}$	$\boldsymbol{r}$
1	*UC*	Copeland (1)
2	Copeland (1)	Markovian
3	Copeland (3)	CIP, Copeland (2), Copeland (3)
4	Copeland (2)	
5	CIP	
6	*MES*	*UC*
7	Markovian	ImWMT, *MES*
8	ImWMT	
9	ImWMVA	ImWMVA
10	MVApc	MVApc
11	MXsh	MXsh
12	MHXsh	MHXsh
13	MHVAsh	MHVAsh
14	MVAsh	MVAsh
15	MXpc	MXpc

The following observations can be made. In all cases aggregate rankings represent the set of single-factor based rankings better than any one of latter do. Therefore replacing eight single-factor rankings by aggregate rankings is justified.

The ranking based the 1st version of the Copeland rule in both cases performs better than the CIP ranking, but the former correlates with the latter better than any of other aggregate ranking does.

6 Conclusion

The Competitive Industrial Performance index is an aggregate of eight observable variables. Its aggregation formula is semi-ordinal. It is cardinal in its form but it is derived from a purely ordinal proposition: the value of an aggregate index should be a strongly increasing function of each of its factors. Only binary comparisons of these values (and not the values themselves or values of their differences or fraction) are meaningful.

Therefore it was interesting for us to test the robustness of the final ranking by replacing the original aggregation formula with purely ordinal methods. We propose to consider aggregation as a multicriteria decision problem and to employ ordinal ranking methods borrowed from social choice to solve it. In this paper we apply two direct ranking methods based on the majority relation (the Copeland rule and the Markovian method) and a multistage procedure of selection and exclusion of the best alternatives, as determined by a majority relation-based social choice solution concept (tournament solution), such as the uncovered set and the minimal externally stable set.

The Markovian ranking is characterized by high level of discrimination - it separates all 135 countries. The sorting by uncovered set and by the minimal externally stable set produced a rough division of countries into large groups - both rankings contain only 23 ranks. Intuitively, these 'rough' orderings seem to be more attractive as representations of relevant differences in industrial competitiveness of nations. The ability to produce such 'rough' rankings can be considered as a strength of the approach proposed.

We use the same method of binary comparisons based on the majority relation to analyse rank correlations. The correlation analysis has shown that aggregate rankings are better representations for the set single-factor rankings than any one of the set. Therefore, replacing single-factor rankings by an aggregate ranking is justified. Though the high level of correlations of all aggregate rankings confirms, apparently, that the original version based on the CIP index is robust, it has also been demonstrated that some of the new aggregate rankings represent the set of criteria better.

The overall conclusion would be the following. Given the large number of different aggregation models and methods and high uncertainty concerning values of their parameters, it seems that much deeper theoretical work is needed to clarify what the national competitiveness really is and how we should measure it.

Appendix

Table 6. Ranks of countries in single-factor-based and aggregate rankings (countries are ordered as in the CIP ranking)

	MVApc	MXpc	MHVAsh	MVAsh	MHXsh	MXsh	ImWMVA	ImWMT	the CIP index	the Copeland r. (1)	the Copeland r. (2)	the Copeland r. (3)	sorting by *UC*	sorting by *MES*	Markovian
Number of positions in a ranking	**135**	**135**	**132**	**133**	**135**	**133**	**99**	**99**	**126**	**117**	**89**	**80**	**23**	**23**	**135**
Japan	2	28	6	21	2	14	3	4	1	1	1	1	1	1	1
Germany	11	9	4	29	8	33	4	2	2	5	4	4	2	2	5
USA	8	39	9	55	15	52	1	3	3	8	7	6	1	1	8
South Korea	10	16	8	7	6	1	5	6	4	3	2	3	1	1	4
Taiwan (China)	7	15	3	6	7	4	10	11	5	2	2	2	1	1	2
Singapore	1	1	1	14	10	23	28	18	6	4	3	3	1	1	3
China	54	54	24	2	20	2	2	1	7	9	10	4	2	1	6
Switzerland	3	5	35	30	9	15	24	16	8	6	5	5	2	2	7
Belgium	14	2	19	52	31	30	26	9	9	11	8	8	2	3	12
France	21	23	13	73	14	27	7	5	10	12	9	8	3	3	11
Italy	22	24	27	53	33	14	8	7	11	16	14	10	4	4	18
Netherlands	17	6	25	71	30	56	23	8	12	13	11	9	3	3	21
Sweden	5	7	10	25	25	24	20	21	13	7	6	6	2	2	9
UK	19	31	20	83	17	47	6	10	14	17	15	11	4	4	14
Ireland	6	4	2	15	34	13	31	26	15	10	7	7	2	2	10
Austria	9	8	22	31	22	32	25	24	16	14	12	9	3	3	22
Canada	20	26	31	78	29	77	13	13	17	23	18	15	5	5	26
Finland	4	11	14	13	40	17	29	32	18	15	13	10	4	3	16
Spain	30	32	36	75	26	40	14	14	19	25	18	17	5	5	27
Czech Republic	27	12	17	8	11	18	38	25	20	18	15	12	4	4	15
Malaysia	34	27	21	10	16	41	27	17	21	22	17	14	5	5	17
Mexico	43	44	28	45	4	46	12	12	22	26	19	16	5	5	25
Thailand	40	40	11	1	19	39	19	19	23	20	16	12	2	1	13
Denmark	13	10	41	72	37	60	39	31	24	29	22	18	5	4	28
Poland	33	36	33	17	24	28	22	22	25	28	20	17	6	5	29
Israel	18	21	5	60	28	3	37	34	26	19	16	11	3	3	24
Slovakia	25	13	18	9	13	6	48	33	27	21	17	13	5	4	20
Australia	24	33	54	91	89	89	21	28	28	31	25	20	7	6	30
Hungary	38	20	7	19	5	31	49	30	29	24	19	14	7	5	19
Turkey	42	52	42	23	49	29	15	27	30	30	21	19	6	6	34
Norway	15	22	52	100	36	112	42	43	31	34	27	22	9	6	32
Slovenia	23	14	12	20	18	19	57	48	32	27	20	16	5	5	23
Brazil	57	72	34	64	59	72	11	23	33	36	29	24	7	6	35
Portugal	32	34	55	69	51	22	44	41	34	33	26	22	8	6	44
Argentina	31	62	45	43	45	84	17	42	35	32	24	21	8	6	38
Russia	60	57	53	39	79	100	18	20	36	38	30	26	7	6	39
Saudi Arabia	39	46	23	80	61	116	30	35	37	35	28	23	8	7	40
Indonesia	77	85	30	11	68	80	16	29	38	38	36	21	8	6	36
Kuwait	26	25	75	89	103	94	55	46	39	45	35	31	10	7	51
Belarus	50	41	73	3	54	26	51	47	40	36	28	25	8	6	46
South Africa	58	58	61	54	43	70	33	37	41	39	31	26	8	6	43
Luxembourg	16	3	117	113	56	35	77	62	42	48	41	28	10	6	42
India	103	104	32	51	70	38	9	15	43	42	35	26	7	6	37

Philippines	79	79	15	18	3	8	34	38	44	32	23	22	8	5	31
Chile	46	48	71	50	107	88	43	44	45	44	34	30	10	7	59
Romania	75	45	37	66	32	21	54	39	46	37	30	25	8	6	45
Lithuania	47	30	74	32	57	36	69	51	47	43	33	29	10	7	50
New Zealand	29	37	87	70	86	91	52	57	48	50	40	33	12	6	52
Greece	36	50	78	101	58	58	46	54	49	46	38	29	11	8	48
Croatia	44	42	40	44	38	20	61	64	50	40	32	27	8	7	49
Venezuela	51	66	36	41	117	108	36	49	50	48	37	32	10	7	62
Estonia	45	19	46	49	50	34	82	63	51	42	35	26	10	7	41
Ukraine	88	59	63	22	47	37	50	40	52	41	32	28	10	6	53
Vietnam	96	78	66	12	72	68	45	36	53	53	43	34	11	7	66
Iran	72	86	24	42	81	104	35	45	54	52	42	33	11	7	58
Costa Rica	41	51	80	24	23	59	60	70	55	47	38	30	8	7	47
Qatar	28	17	77	130	71	124	78	65	56	60	45	41	11	6	55
Tunisia	62	53	99	38	46	43	58	58	57	49	39	33	10	6	54
Bulgaria	69	47	47	48	62	65	70	56	58	51	41	33	11	7	57
Trinidad and Tobago	52	29	26	103	92	57	84	68	58	55	46	36	12	9	56
Malta	37	18	16	86	27	9	92	78	59	33	26	22	8	6	33
Egypt	71	100	56	34	74	76	32	53	60	54	44	35	11	7	68
Peru	66	75	84	59	124	85	47	50	61	61	48	40	12	7	75
Colombia	67	93	65	67	60	107	41	59	62	61	47	41	12	7	76
Iceland	12	35	86	84	44	113	83	90	63	69	53	45	12	7	77
Morocco	84	81	57	68	55	50	53	57	64	59	45	40	11	6	73
Hong Kong (China)	64	56	39	132	35	83	66	66	65	57	46	37	11	7	79
Latvia	63	38	64	96	63	45	85	69	66	59	46	39	11	9	65
Oman	48	49	79	104	48	122	73	72	67	67	50	44	13	10	80
Kazakhstan	74	65	106	65	52	118	56	61	68	63	47	43	13	6	78
El Salvador	59	77	70	16	97	25	65	76	69	62	50	40	11	7	67
Jordan	68	67	48	40	41	48	73	74	70	58	46	38	11	7	60
Uruguay	35	74	88	57	85	98	61	81	71	68	51	46	13	9	81
Pakistan	104	110	51	35	111	44	40	52	72	56	45	37	11	7	69
Lebanon	56	68	69	99	42	62	72	79	73	65	51	42	11	7	61
Serbia	99	64	68	46	64	49	81	67	74	66	48	44	11	7	71
Guatemala	86	84	81	74	88	67	68	71	75	73	54	50	13	7	88
Bangladesh	107	111	67	37	127	12	46	60	76	66	53	41	12	6	70
Mauritius	55	55	124	47	131	5	86	88	77	71	58	44	14	11	63
Sri Lanka	94	89	92	61	113	66	64	71	78	77	59	52	14	10	91
Syria	90	98	59	58	84	92	62	73	79	74	56	50	14	7	85
Algeria	100	83	94	116	133	114	59	55	80	79	61	53	14	11	89
Bosnia and Her-zegovina	89	60	43	90	83	61	88	78	81	70	52	48	13	9	83
FYR Macedonia	70	63	83	33	91	74	88	85	82	72	55	48	13	10	84
Swaziland	61	61	132	4	69	10	91	91	83	64	49	43	11	10	64
Botswana	95	43	58	127	125	7	94	75	84	76	63	49	14	11	82
Ecuador	83	92	102	63	82	117	67	77	85	78	60	53	14	11	93
Cyprus	49	73	91	114	21	55	88	94	86	73	57	47	14	10	72
Côte d'Ivoire	106	102	82	36	65	99	75	77	87	80	62	53	12	7	86
Cambodia	105	97	131	27	118	73	80	77	88	83	66	54	15	13	90
Honduras	80	106	104	26	73	95	74	89	89	79	61	53	14	12	92
Bolivia	97	91	116	62	130	96	79	80	90	84	66	56	15	13	94
Jamaica	81	82	72	108	123	11	89	90	91	81	64	52	14	13	95
Albania	87	88	85	85	94	54	89	90	92	82	62	55	14	10	103
Nigeria	125	108	38	125	120	119	63	50	93	88	70	59	15	11	87
Georgia	102	99	60	88	39	53	91	92	94	84	65	57	15	13	96
Cameroon	101	113	96	28	108	105	71	89	95	86	69	58	15	13	102
Armenia	91	101	110	56	78	69	91	93	96	85	67	58	15	13	104
Paraguay	93	105	89	76	104	119	83	92	97	87	70	58	15	13	98
Congo	110	76	125	120	1	101	95	83	98	90	70	60	16	14	100

Kenya	115	114	119	93	77	86	76	82	99	91	71	62	15	13	97
Senegal	112	107	76	87	101	64	89	87	99	89	68	61	15	13	108
Barbados	78	69	29	128	53	16	98	97	100	75	55	51	11	10	74
Gabon	92	70	113	126	110	121	95	90	100	93	72	63	16	13	109
Fiji	82	87	112	81	112	82	96	96	101	92	72	62	15	15	106
Tanzania	116	117	129	92	102	87	75	86	102	96	73	65	16	13	112
Azerbaijan	109	95	108	129	93	128	91	84	103	94	72	64	16	15	115
Suriname	76	71	93	94	114	123	97	96	104	94	74	61	16	13	99
Mongolia	111	80	114	105	132	75	97	89	105	97	73	66	16	15	111
Panama	73	112	109	117	96	106	83	97	106	95	74	62	16	14	101
Zambia	117	109	62	93	100	120	91	88	107	95	72	65	16	13	113
Macao (China)	53	94	122	131	121	93	93	98	108	105	80	70	17	16	118
Belize	65	90	74	77	134	110	97	98	109	98	76	64	17	15	107
Moldova	113	103	111	98	105	79	96	94	110	99	75	66	17	15	110
Tajikistan	108	124	126	5	12	126	91	97	111	104	82	68	17	16	122
Madagascar	122	118	123	73	128	63	91	93	112	101	77	67	17	15	116
Kyrgyzstan	118	115	118	82	90	115	96	96	113	103	78	70	18	16	121
Ghana	123	119	130	106	76	127	90	93	114	106	78	71	17	16	129
Nepal	127	121	127	110	87	51	91	93	114	103	80	69	17	16	117
Uganda	124	125	95	109	95	102	87	95	115	102	79	68	17	16	114
Yemen	121	120	121	118	122	130	88	94	116	107	80	72	17	16	128
Mozambique	114	127	97	79	115	131	85	97	117	107	81	71	17	16	124
Saint Lucia	85	96	103	124	67	78	98	99	117	100	78	65	17	15	105
Cape Verde	98	116	44	102	135	81	98	99	118	107	81	71	19	16	127
Malawi	128	123	90	97	99	111	95	96	119	108	82	73	19	16	119
Haiti	120	130	115	95	129	42	94	98	120	111	85	75	19	18	125
Sudan	119	129	101	112	126	132	80	96	120	110	84	74	19	17	120
Niger	132	122	49	121	106	71	97	96	121	109	83	73	17	16	123
Rwanda	126	126	107	115	119	90	96	98	122	113	86	77	20	19	130
Ethiopia	131	133	98	123	66	129	88	97	123	112	86	76	17	16	126
CAR	130	131	100	111	116	109	98	99	124	115	87	79	21	21	132
Burundi	133	134	128	107	80	125	98	99	125	116	88	80	22	22	135
Eritrea	134	135	105	119	98	103	98	99	126	117	89	80	23	23	134
Gambia	129	128	120	122	109	97	99	99	126	114	87	78	21	20	131
Iraq	135	132	50	133	75	133	97	98	126	115	87	79	21	20	133

References

1. Aizerman M.A., Aleskerov F.T. (1983). Arrow's problem in group choice theory // Automation and Remote Control - Vol. 9, P. 127-151.
2. Aizerman M., Aleskerov F. (1995). Theory of Choice. Amsterdam: North-Holland/Elsevier.
3. Aleskerov F., Kurbanov E. (1999). A Degree of Manipulability of Known Social Choice Procedures // Current Trends in Economics: Theory and Applications / Eds. Alkan A., Aliprantis Ch., Yannelis N. N.Y.: Springer-Verlag. P. 13-27.
4. Aleskerov F.T., Pislyakov V.V., Subochev A.N. (2013). Rankings of economic journals constructed by methods from Social Choice Theory: Working paper WP7/2013/03. Moscow: National Research University Higher School of Economics. (in Russian)
5. Aleskerov F. T., Pislyakov V., Subochev A. (2014). Ranking Journals In Economics, Management And Political Science By Social Choice Theory Methods / Working papers by NRU Higher School of Economics. Series WP BRP "Science, Technology and Innovation". 2014. No. WP BRP 27/STI/2014.
6. Aleskerov F.T., Pislyakov V.V., Subochev A.N., Chistyakov A.G. (2011). Rankings of management science journals constructed by methods from Social Choice Theory: Working paper WP7/2011/04. Moscow: National Research University Higher School of Economics. (in Russian)
7. Aleskerov F., Subochev A. (2009). Matrix-vector representation of various solution concepts. Working paper WP7/2009/03. Moscow: SU - Higher School of Economics.
8. Aleskerov F., Subochev A. (2013). Modeling optimal social choice: matrix-vector representation of various solution concepts based on majority rule // Journal of Global Optimization - Vol. 56, Iss. 2, P. 737-756.

9. Arrow K.J., Raynaud H. (1986). Social Choice and Multicriterion Decision-Making. Cambridge (Mass.): MIT Press.
10. Chebotarev P., Shamis E. (1999). Preference fusion when the number of alternatives exceeds two: indirect scoring procedures // Journal of the Franklin Institute - Vol. 336, P. 205-226.
11. Copeland A.H. (1951). A reasonable social welfare function (mimeographed notes). University of Michigan, Ann Arbor (Seminar on Application of Mathematics to the Social Sciences).
12. Daniels H.E. (1969). Round-robin tournament scores // Biometrica - Vol. 56, P. 295-299.
13. Good I.J. (1971). A note on Condorcet sets // Public Choice - Vol. 10, P. 97-101.
14. Kendall M.G. (1938). A New Measure of Rank Correlation // Biometrika - Vol. 30, P. 81-89.
15. Laslier J.F. (1997). Tournament Solutions and Majority Voting. Berlin: Springer.
16. Miller N.R. (1980). A new solution set for tournaments and majority voting: Further graph-theoretical approaches to the theory of voting // American Journal of Political Science - Vol. 24, P. 68-96.
17. von Neumann J., Morgenstern O. (1944). Theory of Games and Economic Behavior. Princeton: Princeton University Press.
18. Schwartz T. (1970). On the Possibility of Rational Policy Evaluation // Theory and Decision - Vol. 1, P. 89-106.
19. Schwartz T. (1972). Rationality and the Myth of the Maximum // Noûs - Vol. 6, P. 97-117.
20. Schwartz T. (1977). Collective choice, separation of issues and vote trading // The American Political Science Review - Vol. 71, No. 3, P. 999-1010.
21. Smith J. (1973). Aggregation of Preferences with Variable Electorates // Econometrica - Vol. 41, Iss. 6, P. 1027-1041.

22. Subochev A. (2008). Dominant, Weakly Stable, Uncovered Sets: Properties and Extensions: Working paper WP7/2008/03. Moscow: SU - Higher School of Economics.

23. Tyson L. (1992). Who's Bashing Whom: Trade Conflict in High Technology Industries. Washington: Institute for International Economics.

24. UNIDO (2013). Industrial Development Report 2012/2013. Vienna: UNIDO.

25. Ushakov I.A. (1971). The problem of choosing the preferable object // Izvestiya Akademii Nauk SSSR. Tekhnicheskaya Kibernetika - Vol. 4, P. 3-7. (in Russian)

26. Ward B. (1961). Majority Rule and Allocation // Journal of Conflict Resolution - Vol. 5, P. 379-389.