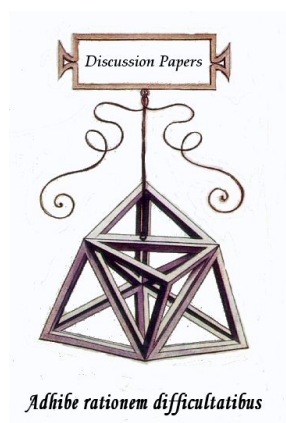




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Communicating the uncertainty of synthetic indicators: a reassessment of the HDI ranking

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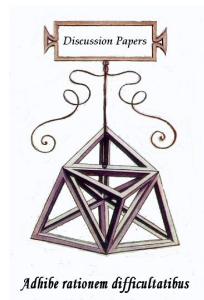
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Tommaso Luzzati, Bruno Cheli, Gianluca Gucciardi

Abstract

Composite indicators convert information about different facets of a given phenomenon into a single figure. Unavoidably, the “conversion process” involves a high level of arbitrariness, which, in general, makes the results not robust. The approach to composite indicators used in this paper aims at mitigating this problem and makes final users more aware of the unavoidable uncertainty of the results (e.g. rankings) based on a given composite. We illustrate our approach by applying it to the Human Development Index.

Keywords: Human Development Index, complexity, composite indicators, robustness, uncertainty analysis.

JEL: C430 Index Numbers and Aggregation Leading indicators; Q010 Sustainable Development; I310 General Welfare

1. Introduction

Rankings have become very popular not only in sports but in many domains of social and economic life. The most used approach is to build rankings by using composite indicators. The question why composites and rankings became so widespread is less trivial than it might appear. Obviously, rankings serve the purpose of evaluating objects that are not immediately comparable to one another due to their multidimensional nature. In some cases, e.g. sport competitions, composites easily accomplish this task and the rules used to calculate the composite indicator are a substantial part of the game. Why using composites beyond a context of games is less obvious. Why do we build composites for questions “Which is the best city to live in?” “How does a given university perform?”. A common answer is benchmarking, i.e., comparing performances to one another in order to stimulate progress. To this purpose, however, it is necessary to go deep into each aspect of the synthetic performance as measured by the composite. This points out the core issue regarding composites, which is the loss of relevant information when heterogeneous pieces of information are combined together. It is true that our capability of processing information is limited, as, for instance, the work of Herbert Simon has emphasised (e.g. Simon, 1978). This limitation, however, does not imply the necessity of getting to the extreme level of synthesis, that is, to condense all the information into a single number. In fact, this is against rationality and against everyday experience. When buying a smartphone, a car, a laptop, nobody asks the expert for a single number to describe each alternative, we are rather interested in the specific features of the alternatives. Similarly, when looking for a hotel on the Internet, we give a glimpse at the global ranking, but we commonly choose the accommodation on the basis of those criteria that are most relevant to our personal needs and tastes.

Surprisingly, when the evaluation falls within the sphere of public debate, the reduction to a single figure is a very common practice, as in the case of Cost-Benefit analysis where the different aspects of each alternative project are summarised into a single figure. This is surprising since more robust methodological approaches are available, such as multi-criteria evaluation methods (see, e.g., Munda 2008). Paradoxically, also the theoretical debate suggests that is not a good idea to build a ranking by reducing all the information to a single figure. Actually, rank building can be easily seen as the social choice problem of aggregating individual preferences into a social ordering. The debate on this dates back at least to the end of the 18th century, that is, to the Borda-Condorcet controversy (see e.g. Brian, 2008). After Kenneth Arrow’s impossibility theorem, one can safely affirm that no method for establishing a complete order is perfect.

The well-known Index of Human Development¹ (HDI) is an example of this “mania” for a single number. As for any composite indicator, its extremely synthetic nature is a major reason both for its success (see, e.g., Paruolo et al., 2013) and for well-founded criticism. By using HDI as an example, this paper aims to show that composites can be used in a wider perspective than the traditional one so as to (i) reduce the arbitrariness related to the choice among alternative normalization and combination rules, and (ii) avoid a simplistic view of the phenomenon under inquiry by communicating the intrinsic² uncertainty of the outcome involved by a single composite. To this purpose, similarly to Saisana and Munda (2008), Floridi et al. (2011), and Luzzati and Gucciardi (2015), we put uncertainty analysis at the centre of both the methodological approach and the substantive analysis. First we calculated many different composites, and their related rankings, according to different normalization and aggregation rules. Then we computed the frequency distribution of the different ranks got by each Country and calculated a plausible range for them. We also performed a clustering analysis, again under different standardisation rules, and checked if it could help in improving the uncertainty analysis, in particular whether it could be useful for testing the validity of the cut-off points currently used to classify different level of Human Development.

Not many papers have addressed the issue of the robustness of the HDI. Cahill (2005), Herrero et al. (2012), Klugman et al. (2011), Morse 2014, and Zambrano (2011) are among them. The purpose of these papers was to contribute to the debate on the methodological assumptions at the basis of the calculation of the HDI. The paper by García and Kovacevic (2010) is particularly relevant here since they followed the same approach that inspired the work presented in this paper, that is, the approach set forth in the guidelines for constructing composite indicators elaborated by the OECD and JRC (Nardo et al., 2008) and in several other works by members of composite indicators research group of the JRC of the European Commission. Our work, however, has a more limited scope than that by García and Kovacevic (2010). We will discuss similarities and differences when appropriate and relevant.

¹ The HDI has been published since 1990 by the United Nations Development Program (UNDP) in its yearly Human Development Report. As well known, the purpose of HDI is to capture the development of a country on the basis of three dimensions - “health”, “knowledge” and “standard of living”. After some changes in the methodology that have been made in the past years, HDI is calculated as the geometric mean of normalized indices for each of its three dimensions.

² Such uncertainty derives from the above-mentioned arbitrariness related to the choice among alternative normalization and combination rules that are used to construct the composite. It also depends on other issues that we do not discuss here, such as the choice of the relevant set of information.

The paper is organised as follows. Section 2 illustrates the methods that we used, section 3 reports and shortly discusses the results of the uncertainty analysis, section 4 contains the cluster analysis, section 5 concludes.

2. Methods

Uncertainty analysis aims at understanding the effects of “non essential” changes in the method of calculating the index. The term “non essential” refers to assumptions that can be justified neither by some data properties nor by theoretical reasons. García and Kovacevic (2010) developed their analysis by considering as non essential (i) the functional form of life expectancy (whether log transformed or not), (ii) the minimum goalposts for income and life expectancy, and (iii) the weighting system. They kept the geometric aggregation assumption and the rule of data normalization³. As a result they obtained many possible indexes, which are, however, comparable among them due to the homogeneity of their aggregation and normalization rule.

The uncertainty analysis that is performed here is wider for two reasons. Firstly, although we are in favour of aggregation rules that reward balanced achievement in all dimension and limit substitutability, such as the geometric one, we also acknowledge (i) the theoretical reasons that justified using the linear aggregation for 20 years and (ii) the existence of other are interesting aggregation rules that are in between the geometric and the linear one. Secondly, we used also other normalization rules that do not contrast with the spirit of the HDI. Hence, our uncertainty analysis is based on varying the normalisation rule, the aggregation rule, and the weighting system.

We retained all the other methodological assumptions, in particular

- 1) the diminishing returns from income for human development, which involves using the logarithm of Gross National Income;
- 2) the existence of some goalposts, the ‘natural zeros’ and ‘aspirational goals’ (HDI 2015, p.2), which are, respectively, 20 and 85 years for Life Expectancy, 0 and 16.5 years⁴ for Education, and 100\$ and 75,000\$ (at 2011 PPP) for GNI.

To keep those assumptions, we transformed the raw data available from to UNDP website as follows:

³ HDI normalisation is a sort of “distance from the leader” (Nardo et al, 2008) calculated after rescaling data for considering the minimum and maximum goalposts.

⁴ Education is made of two components, the years of schooling for adults aged 25 years and more and the expected years of schooling for children of school entering age. The first indicator is capped at 15 years, the second at 18. Since they are linearly aggregated with equal weight, we made an average of their respective goalposts, i.e. 0 and 16,5, and rescaled them accordingly.

- (i) we subtracted 20 years from Life Expectancy,
- (ii) we capped income to 75,000\$ and used the difference between the logarithm of income and subtracted the logarithm of 100\$
- (iv) we rescaled the education indicators as explained in footnote 3.

As emphasised in the mentioned OECD and JRC guidelines for composite indicators (Nardo et al., 2008), both standardisation and aggregation rules are very important. As we stated above, we combined different normalization and aggregation rules, as well as different weighting systems, in order to calculate many alternative composites and performed an uncertainty analysis of the HDI.

We started by considering three aggregation rules, that is, the linear, the geometric, and the concave one⁵, as defined by Casadio, Tarabusi and Palazzi (2004). The concave one is a kind of compromise between the linear and the geometric one. It is close to the linear one when performances are high, while strongly punishes low performances. In practice, while the geometric aggregation punishes unbalanced performances, the concave one does it only when performances are poor. The aggregation rules are defined in Table 1.

Concerning the normalization rules, we chose⁶ the z-score, the min-max, and the normalization that is currently in use for the HDI. We rescaled the z-score and the min-max as indicated in Table 2. We did so for two reasons, firstly in order to exclude negative and zero values so that they are suitable for the concave and the geometric aggregation rules, secondly in order to have ranges of variation, means and standard deviations similar to the ones got with the HDI normalization⁷.

⁵ An interesting rule is contained in the Mazziotta-Pareto Index (de Muro et al. 2011). We did not use it since with this particular dataset it would have given results too similar to the linear aggregation case.

⁶ The OECD and JRC guidelines to the construction of composite indicators consider three more normalization rules that we did not use in this context. They are the so-called Borda Count, the Distance from the leader and the Distance from the average. The Borda Count was not used here because it rescales the performances according to equal intervals, which is contrary to the purpose of using partially non-compensatory aggregation rules, which leads to punish performances that are bad in absolute terms. The “distance from the leader” (the ratio between the indicator and the best performance) was not used since in this case it would be almost identical to the HDI normalization. The same occurs when the “distance from the average” is used with geometric aggregation.

⁷ We report below the averages over the three dimensions of the statistics of the data normalised with the three rules that we used.

	<i>HDI</i>	<i>z-score</i>	<i>min-max</i>
<i>mean</i>	0,70	0,68	0,68
<i>st dev</i>	0,16	0,18	0,19
<i>min</i>	0,30	0,23	0,20
<i>max</i>	0,97	0,98	1,00

Table 1: Aggregation rules

<i>Name</i>	<i>Rule</i>
Linear:	$CI_i = \sum_{q=1}^Q w^q I_i^q$
Geometric:	$CI_i = \prod_{q=1}^Q (I_i^q)^{w_q}$
Concave:	$CI_i = \sum_{q=1}^Q w^q (I_i^q - h e^{-k I_i^q})$

Where I_i^q is the normalised indicator for variable q and Country i , w stands for the weight, and h and k are parameters that we set here equal to 1.

Table 2: Normalization rules

<i>Name</i>	<i>Rule</i>	<i>Range</i>
z-score	$I_i^q = \frac{a + b(x_i^q - \bar{x}^q)}{\sigma^q}$	$av(I)=a/10$ $\sigma(I)=b/10$
HDI normalization	$I_i^q = \frac{x_i^q}{AspG_i}$	[0.2;1]
Min-max	$I_i^q = \left[\frac{x_c^q - \min(x^q)}{\max(x^q) - \min(x^q)} + \beta \right] * a$	[0.2;1]

Where

I_i^q is the normalised indicator for variable q and Country i

$AspG$ is the aspirational goal set in the HDI

\bar{x} is the average, σ the standard deviation, \min and \max are respectively the highest and the lowest value of the indicator q across Countries.

Notice that the x data are not raw. They are already rescaled in order to take into account the HDI 'goalposts' and the diminishing returns from income.

We set $a=68$, $b=18$, $\alpha=0.8$ and $\beta=0.25$

The HDI is meant not only to compare countries but also to assess changes of a single Country by comparing its HDI values over time. Only looking at a Country's position might be misleading since we could observe a decrease in the ranking (or vice versa), even though its absolute performances improve (or vice versa).

As for the HDI, we gave equal weight to each of the three dimensions. However, we also considered a kind of Benefit-of-the-Doubt approach⁸ (see, e.g., Melyn and Moesen, 1991) by assigning a 0.2 weight to the worst of the three component indices and 0.4 to the other two. Hence, using the dataset available from the HDI website, we built 1,701 composites, three composite per each aggregation rule plus other nine for each of the 188 countries.

3. Results

It has to preliminary be highlighted that, the choice of using several normalization and aggregation rules makes both the range of variations and the meaning of our different indexes slightly different from each other, differently from García and Kovacevic (2010). For this reason, we prefer to focus only on ranks rather than on the values taken by the different indexes. The main results are illustrated by referring to Figures 1, 2 and 3. Usually, graphs are built by putting the HDI values or ranks on the x-axis and the distribution resulting from the uncertainty analysis on the y-axis. This however, does not allow to easily reading the name of each country. For this reason, we preferred to invert the axis and list on the y-axis the 188 countries, ordered according to their place in the HDI ranking, from the first to the last. The horizontal axis displays all the possible ranks from 1 to 188. In correspondence of any Country we have a horizontal string of one or more coloured squares, each of them telling also the frequency of the rank of the uncertainty exercise. This can be seen by looking at Figure 1 that focuses on the situation of the first 15 Countries.

The first column contains the HDI rank, the second one contains the median of the frequency distribution, the third one, labelled with “high”, contains the 10th percentile and the fourth one, labelled with “low”, contains the 90th percentile. We can see that Norway is always at the first place of the ranking whichever is the composite we look at; Australia is at the 2nd place according to some composites (for the 68% of them) and at the 3rd according to other ones (for the 32% of them), and so on. Each row represents the frequency distribution of the ranks for the corresponding Country, where the darker the square, the higher the number of composites that determine that particular rank. In general, one notices that the picture is rather different from the one observed by looking at the HDI only. For instance, the Netherlands, that ranks 5th according to the HDI (first column), has a median rank of 7 in our uncertainty exercise.

⁸ This is made, for instance, to consider that historical reasons could make very difficult for a Country to change its performances in one of the dimensions.

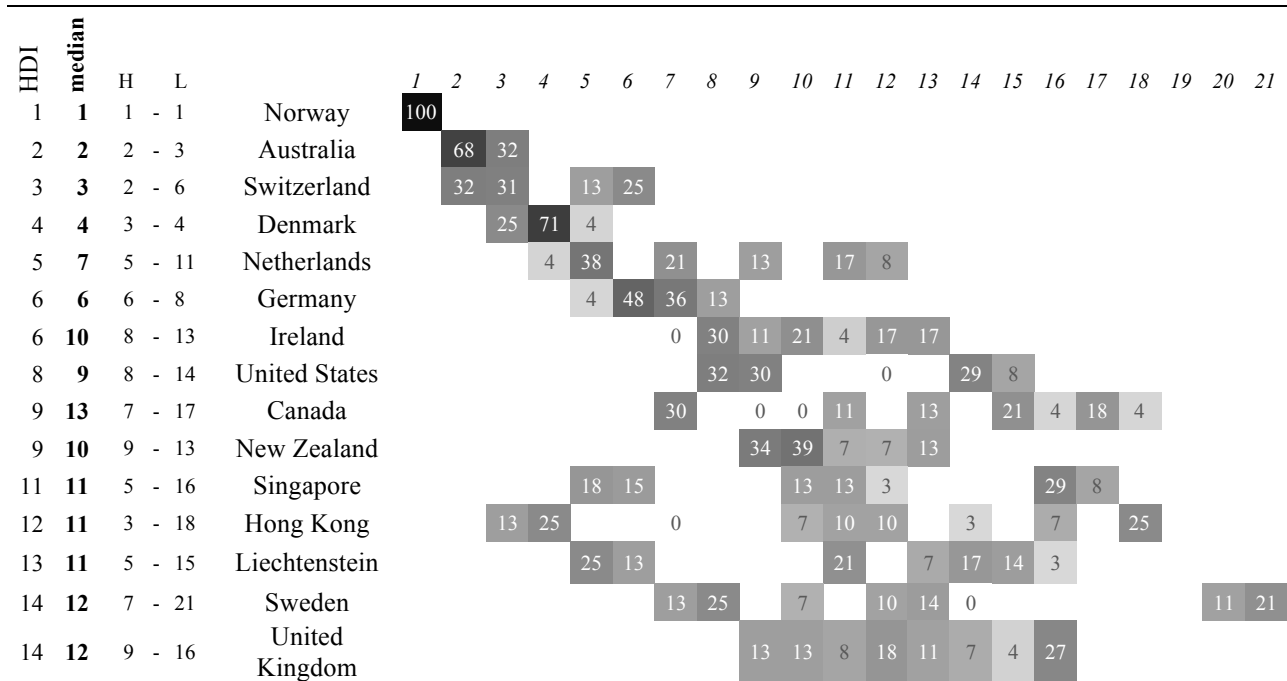


Figure 1. Frequency distributions of the rankings for the 15 countries with highest HDI values.

Figure 2 zooms out to all Countries in order to provide an overview of the overall effect of the uncertainty exercise. As explained before, the frequency distribution of the 1,701 ranks for each country is drawn on its corresponding row. For some country the distribution is concentrated and centred around the main diagonal. This indicates that the HDI rank of that Country is robust, i.e., it does not change much when the method of building the composite changes. In other cases, the distribution is still rather centred around the diagonal, but with more dispersion. In these cases the HDI rank is still close to the median, and therefore representative of the uncertainty exercise, but not very robust to change. Finally, we have countries for which the frequencies are dispersed and the HDI rank is quite close to one extreme of the frequency distribution. In the latter case the HDI rank is not robust.

Figure 3 gives a visualisation of the partial effects of using separately only the 9 basic indicators (left picture) and only the HDI with the Benefit of the Doubt weighting (189 composite, right picture). By looking at the horizontal positions of the coloured squares, one can guess that the range of the possible ranks becomes wide in both partial cases. To have a quantitative indication, for each Country we calculated the range of the ranks between the 10th and the 90th percentile. They sum to 666 when considering the nine basic composites, to 1540 for HDI with BOD weighting, and to 1904 when including all composites.

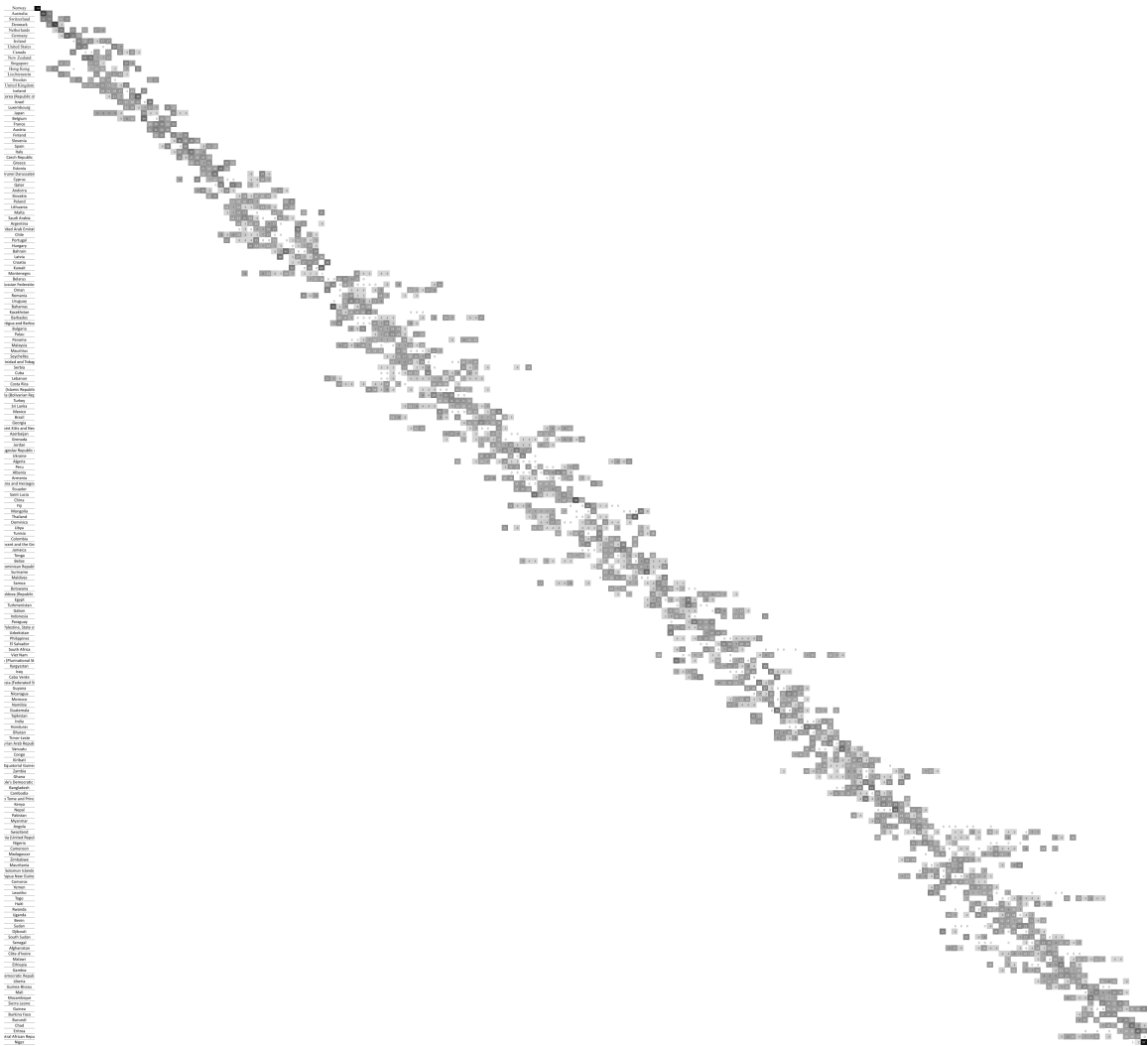


Figure 2. Frequency distributions of the rankings for each country

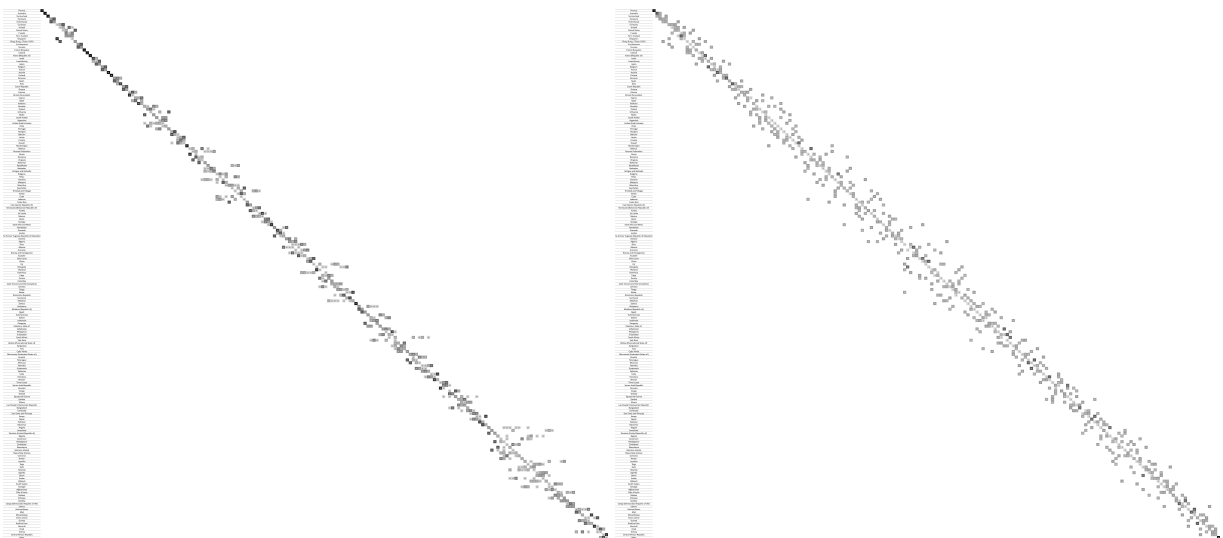


Figure 3. Frequency distributions of the ranks for the 9 basic indicators (left) and for HDI with BOD only (right)

In our opinion, only a range of plausible ranks should be communicated, for instance the ranks between the 10th and the 90th percentile as shown in Table 3, where Countries are listed according to the median of the frequency distribution of their ranks.

Table 3: Range of plausible ranks for the first 15 HDI ranked Countries

	H	L
Norway	1	1
Australia	2	3
Switzerland	2	6
Denmark	3	4
Germany	6	8
Netherlands	5	11
United States	8	14
Ireland	8	13
New Zealand	9	13
Hong Kong	3	18
Liechtenstein	5	15
Singapore	5	16
Sweden	7	21
United Kingdom	9	16
Canada	7	17

In the appendix, Table A1 reports the median ranks, and the 10th and the 19th percentiles for all countries.

Finally, one could ask which of the 9 basic composite indicators that we used best represents the ranking indicated by the medians of our uncertainty analysis. To do this we calculated the average rank shift⁹ when moving from the rank of a particular composite to our median rank, that is,

$$\frac{1}{188} \sum_{i=1}^{188} |m_i - r_i|$$

where i indicates the i -th Country, m_i its median rank and r_i its rank according to one particular composite.

As a result, the composite that is closest to the ranking involved by our analysis are those based on HDI normalization, also in the concave and linear aggregation. Table 4 shows for each of the basic composites the distance of their rankings with respect to our median ranking, measured both by the Euclidean Distance and Average rank change.

⁹ This makes possible a comparison with Garcia and Kovacevic (2010, p. 22). For them the average rank shift is from 2 to 4 depending on the group of Countries.

Table 4. The distance between the median ranking and each ranking from the 9 basic indicators

<i>Index:</i>	<i>HDI</i>	<i>HDI concave</i>	<i>HDI linear</i>	<i>z-score linear</i>	<i>z-score concave</i>	<i>z-score geom</i>	<i>min-max linear</i>	<i>min-max concave</i>	<i>min-max geom</i>
Av. rank change:	2.26	2.51	2.71	3.50	3.63	3.67	3.52	3.59	3.40

Table 5 gives more details than table 4. For the first 15 Countries it focuses on the ranks from respectively “HDI”, “HDI-Concave” and “Minmax-Geom”. We used the symbols ✓, ♢ and ♡ to visualize the difference between the rank according to each single composite and the median rank. More precisely, ♢ indicates that the composite assigns the country a better rank than our median, while ♡ a worse rank. A ✓ indicates that the absolute difference is 0 or 1, whereas a ♢ or a ♡ means that the absolute difference is 2 or 3. Finally we use ♢♢ or ♡♡ when the absolute difference is higher than 3.

Table 5: A focus on the comparison between the median rankings and each of the ranking from the 9 basic indicators; first 15 Countries

	<i>median rank</i>	<i>HDI</i>	<i>HDI-concave</i>	<i>Minmax-geom</i>
Norway	1	1 ✓	1 ✓	1 ✓
Australia	2	2 ✓	2 ✓	2 ✓
Switzerland	3	3 ✓	3 ✓	3 ✓
Denmark	4	4 ✓	4 ✓	5 ♡
Netherlands	7	5 ♢♢	5 ♢♢	4 ♢♢
Germany	6	6 ✓	7 ♡	8 ♡
Ireland	10	6 ♢♢	8 ♢♢	10 ✓
United States	9	8 ♢	9 ✓	12 ♡♡
Canada	13	9 ♢♢	11 ♢♢	9 ♢♢
New Zealand	10	9 ♢	10 ✓	11 ♡
Singapore	11	11 ✓	6 ♢♢	6 ♢♢
Hong Kong, CHN	11	12 ♡	12 ♡	7 ♢♢
Liechtenstein	11	13 ♡♡	13 ♡♡	14 ♡♡
Sweden	12	14 ♡♡	14 ♡♡	13 ♡
United Kingdom	12	14 ♡♡	15 ♡♡	15 ♡♡

4. Clustering the Countries

As García and Kovacevic (2010) did, we conducted a cluster analysis on our dataset in order to identify the similarities and the differences across the performances of the 188 analysed Countries. Since we have not a precise theory to provide an *ex-ante* number of clusters to be tested, we

conduct a hierarchical cluster analysis as recommended by Nardo et al. (2008). We first set the metric of the clustering (i.e., the distance between pairs of observations) as the Euclidean distance. The analysis is then conducted on normalised data so as to avoid the “difference in scale” bias. Consistently with our uncertainty analysis, we considered three different normalization rules, z-score, min-max, and HDI normalizations. We also checked the outcome of the “distance from the mean” normalization.

We adopted the Ward’s method (Ward, 1963) as linkage criterion, in order to calculate the distance between sets of observations. According to this iterative process, at each step clusters or observations are combined in such a way as to minimize the increase in the variance within the groups. In order to establish the number of clusters, we used the Duda and Hart’s (1972) stopping rule¹⁰. Such rule, is based on the ratio $Je(2)/Je(1)$, where $Je(2)$ is the sum of squared errors within cluster when the data are partitioned into two clusters, and $Je(1)$ gives the squared errors when only one cluster is present. Larger values of the $Je(2)/Je(1)$ ratio indicate more distinct clustering. In Table 5, the $Je(2)/Je(1)$ ratios are reported for the four different cluster analysis. The maximum value that determines the number of clusters is emphasised in bold.

As expected, the standardisation rule used for the cluster analysis affects the outcome. As shown in Table 6, according to the different standardisation, countries are grouped in five clusters (for the min-max and the HDI rule), in four clusters (for the z-score), and in eight clusters (for the distance from the mean).

Table 5. Values of the $Je(2)/Je(1)$ ratio in four distinct cluster analysis

Standardization rule	N. of clusters														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Min-Max	0.41	0.49	0.50	0.66	0.72	0.66	0.63	0.49	0.66	0.47	0.61	0.43	0.65	0.63	0.39
Z-Score	0.41	0.49	0.50	0.70	0.66	0.66	0.63	0.49	0.65	0.47	0.61	0.44	0.65	0.59	0.40
HDI	0.43	0.44	0.51	0.67	0.72	0.53	0.69	0.49	0.70	0.67	0.50	0.38	0.55	0.57	0.54
Distance from the average	0.36	0.51	0.52	0.65	0.66	0.52	0.54	0.71	0.65	0.59	0.44	0.55	0.61	0.64	0.68

¹⁰ There exist several other “cluster validation” techniques including the choice minimizing the pseudo T-Square, the use of “internal measures” such as cohesion and separation or a mix of them also known as the “average silhouette width” (Rousseeuw, 1987). The choice of a different technique usually leads to different results in terms of number of clusters (and their composition) and may have relevant implications in the descriptive analysis of the data (Jain and Dubes, 1988). However, for the purposes of this work, the adoption of a different validation technique would not have changed its substantial results.

Table 6. Number and sizes of clusters for each cluster analysis

N. of Clusters	min-max	z-score	HDI stand.	Ratio to the mean
1	29	29	41	34
2	68	69	44	8
3	49	48	40	26
4	29	42	18	44
5	13		45	9
6				22
7				8
8				37

The dimensions of the clusters differ from one another, also when the number of clusters is the same. For instance, according to the min-max cluster analysis we get 5 clusters composed respectively of 29, 68, 49, 29 and 13 countries, while according to the HDI rule the 5 clusters are composed of 41, 44, 40, 18 and 45 countries. Notice also that not only the total number of countries by cluster, but also the composition of the single cluster changes. Overall, it is evident that a seemingly innocuous choice, as the adoption of a particular technique of data normalization, can strongly interfere with the outcome of the analysis of the data.

Comparing clustering resulting from different normalisations different, however, can give important specific indications, as in this case.

A first point to emphasise is that there is a very strong correlation between clusters and their performances in terms of HDI, particularly with the z-score and min-max standardisation. This allows using the cluster analysis to set the cut-off points for different levels of human development achievements.

Secondly, the min max and the z-score rules give almost identical clustering since the only relevant difference is that min-max splits into two groups the fourth group of the z-score rule so that they can be thought of as a subgroup of the last one. This is confirmed by considering that the last group built with the HDI standardisation is almost the same as the last group under the z-score rule. Finally also group 3 and 4 built with HDI standardisation are rather similar and could be re-grouped together. As a result, we suggest keeping the same number of groups chosen in the Human Development Reports, i.e. 4 groups, but changing the respective cut-off points.

Table 7 shows the number of countries and the cut-off points according to (i) the classification used in the 2014 and 2015 Human Development Reports, and those implied by (ii) z-score, (iii) min-

max, and (iv) HDI normalisation rules. The cut-off points involved by the z-score and the min-max are the more or less the same and labelled with “A”, while the ones involved by the HDI standardisation are labelled with “B”. The resulting suggestion is to raise the cut-off points of the Very High and High classes and to lower the cut-off of the Medium human development class.

Table 7. Number of countries in the groups under the current UNRO classification and alternatives ones suggested by our cluster analysis

Group	Current HDI classification	<i>cut-offs points</i>	z-score norm.	min-max norm.	<i>cut-offs points “A”</i>	HDI norm.	<i>cut-offs points “B”</i>
1	49	0.80	29	29	0.865	41	0.835
2	56	0.70	69	68	0.720	44	0.724
3	39	0.55	48	49	0.54	3a) 40 3b) 18	0.512
4	44		42	4a) 29 4b) 13		45	

5. Conclusion

Building a composite index involves an unavoidable uncertainty, similarly and more than adding apples and oranges. The researcher has to make many arbitrary choices, concerning relevant indicators, normalization and aggregation rules, and weighting of the component variables. Hence uncertainty grows with the efforts of synthesising the data, moving away who reads the composite from the intrinsic content of the original data.

The HDI ranking, as shown in this paper and also by the paper that tackle this issue, is rather robust. This is not surprising since only four indicators, which are also rather correlated to one another, are used to calculate it. Still, the HDI is sensitive to small changes in its assumptions.

The difference between our analysis and previous one is epistemological¹¹. We do not assume that the true picture of human development exists. Therefore, we are not interested in assessing whether HDI is biased or not. Biased with respect to what? A synthetic single picture cannot describe multifaceted and complex objects. Some faces can be described by what Georgescu Roegen (1971)

¹¹ For a detailed discussion of what we argue in the next few sentences see Funtowicz and Ravetz (1990) and Giampietro (2003).

named arithmomorphic notions, other by dialectical ones, e.g. quality indicators on an ordinal scale. In any case, different units of measurement involve an unavoidably incommensurability. This, however, does not imply that “nothing can be said”. Uncertainty analysis helps saying something, that is, that a plausible rank range for each country exists. This is sufficiently simple to be understood by the general public, but enough complicated to communicate that no measure of “the true human development” can exist.

Hence, we claim that rather than the HDI rankings, a range of plausible ranks should be communicated together with the HDI figure. This seems to us a reasonable compromise between the need of synthesis when the analysis involves many variables and the loss of relevant information due to composing different indicators into a single index. This would also help the comparison across time of a single country performance, which might reveal an improvement even if the Country does not surpass any other. As a personal comment, we find that making the results more uncertain would also mitigate the idea that building composites is just a nice game to satisfy our passion/obsession for competition.

A second issue that was investigated in this paper is the relationship between the HDI ranking and possible clusters of the Countries. As for the uncertainty analysis, we used different standardisation rules, which involves, as expected, different clustering. Nonetheless, quite a clear picture emerges. First, there is a strict relation between levels of development and clusters. Second, the grouping of the Countries made by the clustering analysis is different from the one currently used in the Human Development Report. The most evident difference is that some of the Countries classified as very highly developed are much more similar to the Countries classified as highly developed. The cluster analysis suggests keeping the division into four groups, but changing their cut-off points.

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Appendix

Table A1. HDI, median rank, 10th and 90th percentile of the uncertainty analysis

	HDI	median	high	low		HDI	median	high	low
Norway	1	1	1	1	Malta	37	41	34	49
Australia	2	2	2	3	Saudi Arabia	39	36	34	43
Switzerland	3	3	2	6	Argentina	40	40	35	46
Denmark	4	4	3	4	United Arab Emirates	41	41	38	45
Netherlands	5	7	5	11	Chile	42	39	33	47
Germany	6	6	6	8	Portugal	43	38	33	47
Ireland	6	10	8	13	Hungary	44	40	37	47
United States	8	9	8	14	Bahrain	45	43	42	48
Canada	9	13	7	17	Latvia	46	45	42	49
New Zealand	9	10	9	13	Croatia	47	48	46	50
Singapore	11	11	5	16	Kuwait	48	47	44	49
Hong Kong	12	11	3	18	Montenegro	49	43	39	57
Liechtenstein	13	11	5	15	Belarus	50	52	48	55
Sweden	14	12	7	21	Russian Federation	50	53	50	69
United Kingdom	14	12	9	16	Oman	52	59	50	67
Iceland	16	15	12	19	Romania	52	54	46	60
R. of Korea	17	17	14	18	Uruguay	52	55	53	58
Israel	18	18	15	20	Bahamas	55	51	51	57
Luxembourg	19	20	16	24	Kazakhstan	56	56	52	57
Japan	20	19	12	24	Barbados	57	68	52	76
Belgium	21	19	16	23	Antigua and Barbuda	58	58	52	64
France	22	22	20	24	Bulgaria	59	59	55	62
Austria	23	21	20	23	Palau	60	62	59	66
Finland	24	24	21	26	Panama	60	63	57	75
Slovenia	25	26	25	28	Malaysia	62	56	53	66
Spain	26	26	23	31	Mauritius	63	62	57	68
Italy	27	27	25	28	Seychelles	64	65	62	67
Czech Republic	28	27	25	30	Trinidad and Tobago	64	66	61	75
Greece	29	30	27	34	Serbia	66	73	61	84
Estonia	30	32	29	33	Cuba	67	67	64	74
Brunei Darussalam	31	31	29	39	Lebanon	67	67	50	74
Cyprus	32	31	28	39	Costa Rica	69	60	52	70
Qatar	32	34	32	37	IR of Iran	69	60	57	74
Andorra	34	33	29	42	Venezuela	71	70	67	71
Slovakia	35	36	30	40	Turkey	72	72	69	74
Poland	36	37	34	44	Sri Lanka	73	72	64	76
Lithuania	37	39	33	44	Mexico	74	75	69	79

Table A1. continued

	HDI	median	high	low		HDI	median	high	low
Brazil	75	72	61	- 80	Paraguay	112	113	112	- 115
Georgia	76	76	74	- 79	Palestine, State of	113	110	108	- 115
Saint Kitts and Nevis	77	79	65	- 91	Uzbekistan	114	115	108	- 117
Azerbaijan	78	78	71	- 88	Philippines	115	114	112	- 123
Grenada	79	84	73	- 93	El Salvador	116	118	117	- 121
Jordan	80	81	78	- 87	South Africa	116	115	110	- 119
Republic of Macedonia	81	82	79	- 84	Viet Nam	116	125	106	- 136
Ukraine	81	78	76	- 83	Bolivia	119	112	109	- 122
Algeria	83	80	72	- 101	Kyrgyzstan	120	119	116	- 124
Peru	84	84	81	- 92	Iraq	121	122	110	- 126
Albania	85	89	85	- 90	Cabo Verde	122	120	112	- 126
Armenia	85	81	77	- 93	Micronesia	123	119	117	- 124
Bosnia and Herzegovina	85	87	82	- 96	Guyana	124	124	121	- 130
Ecuador	88	86	82	- 91	Nicaragua	125	128	124	- 129
Saint Lucia	89	86	85	- 90	Morocco	126	123	119	- 129
China	90	92	90	- 93	Namibia	126	125	118	- 130
Fiji	90	94	81	- 95	Guatemala	128	129	126	- 136
Mongolia	90	95	85	- 103	Tajikistan	129	127	122	- 129
Thailand	93	101	85	- 102	India	130	130	122	- 135
Dominica	94	94	88	- 98	Honduras	131	132	131	- 135
Libya	94	87	80	- 103	Bhutan	132	130	126	- 135
Tunisia	96	96	89	- 105	Timor-Leste	133	132	127	- 136
Colombia	97	96	93	- 102	Syrian Arab Republic	134	135	132	- 138
Vincent and the Grenadines	97	98	94	- 102	Vanuatu	134	137	131	- 139
Jamaica	99	99	97	- 101	Congo	136	134	130	- 140
Tonga	100	98	91	- 105	Kiribati	137	139	134	- 142
Belize	101	101	84	- 105	Equatorial Guinea	138	139	134	- 142
Dominican Republic	101	103	96	- 107	Zambia	139	138	131	- 152
Suriname	103	103	97	- 104	Ghana	140	143	136	- 148
Maldives	104	100	97	- 107	Lao PDR	141	144	140	- 147
Samoa	105	102	86	- 107	Bangladesh	142	140	138	- 142
Botswana	106	106	98	- 109	Cambodia	143	138	136	- 144
Moldova (Republic of)	107	113	101	- 117	Sao Tome and Principe	143	143	141	- 148
Egypt	108	111	105	- 114	Kenya	145	145	144	- 147
Turkmenistan	109	111	105	- 112	Nepal	145	147	146	- 150
Gabon	110	116	108	- 120	Pakistan	147	145	139	- 150
Indonesia	110	117	108	- 124	Myanmar	148	148	143	- 150

Table A1. continued

	HDI	median	high	low		HDI	median	high	low
Angola	149	149	145	- 152	Eritrea	186	186	185	- 187
Swaziland	150	157	145	- 169	Central African Republic	187	180	175	- 186
U.R. of Tanzania	151	160	143	- 176	Niger	188	187	187	- 187
Nigeria	152	151	149	- 155					
Cameroon	153	163	152	- 171					
Madagascar	154	162	153	- 164					
Zimbabwe	155	156	148	- 159					
Mauritania	156	157	154	- 167					
Solomon Islands	156	156	151	- 159					
Papua New Guinea	158	153	148	- 161					
Comoros	159	156	154	- 159					
Yemen	160	159	153	- 162					
Lesotho	161	158	152	- 162					
Togo	162	169	154	- 179					
Haiti	163	165	160	- 171					
Rwanda	163	162	159	- 166					
Uganda	163	161	155	- 168					
Benin	166	166	163	- 171					
Sudan	167	167	164	- 169					
Djibouti	168	163	154	- 170					
South Sudan	169	168	158	- 171					
Senegal	170	172	170	- 176					
Afghanistan	171	161	156	- 172					
Côte d'Ivoire	172	169	166	- 173					
Malawi	173	177	170	- 181					
Ethiopia	174	174	162	- 176					
Gambia	175	170	166	- 177					
D.R. of Congo	176	175	172	- 177					
Liberia	177	177	171	- 183					
Guinea-Bissau	178	178	172	- 180					
Mali	179	182	180	- 184					
Mozambique	180	179	176	- 182					
Sierra Leone	181	182	181	- 185					
Guinea	182	185	179	- 187					
Burkina Faso	183	181	178	- 183					
Burundi	184	184	178	- 186					
Chad	185	186	182	- 186					

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