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Interval Based Composite Indicators

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Summary

Composite indicators are increasingly important in country comparisons and in policy making. At the same time, the robustness of the results obtained and in particular of the rankings and the conclusions obtained from the analysis it is usually accepted with doubts. In this sense our proposal is to use interval data in order to measure the uncertainty related to the different composite indicators based on the different assumptions used as input. In this sense where composite indicators can be considered as models, for this reason it could be necessary to assess the uncertainties related to the different choices in the construction. The uncertainty can be represented by the interval data. The intervals keep the information related to the initial value of the composite indicator, but at the same time give information on the range of the results.

Keywords: Composite Indicators, Interval Data, Robustness, Sensitivity Analysis, Uncertainty Analysis

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Interval Based Composite Indicators

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Abstract Composite indicators are increasingly important in country comparisons and in policy making. At the same time, the robustness of the results obtained and in particular of the rankings and the conclusions obtained from the analysis it is usually accepted with doubts. In this sense our proposal is to use interval data in order to measure the uncertainty related to the different composite indicators based on the different assumptions used as input. In this sense where composite indicators can be considered as models, for this reason it could be necessary to assess the uncertainties related to the different choices in the construction. The uncertainty can be represented by the interval data. The intervals keep the information related to the initial value of the composite indicator, but at the same time give information on the range of the results.

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1 Why Composite Indicators are important

Composite indicators are becoming more and more important in regional or in country comparison on various topics with aim of decision making and in policy-making [17, 3]. Composite indicators can be defined as the aggregation of multiple individual indicators in order to obtain an aggreate measure [19]. Various points in favour and contrary are considered in literature on the construction of the composite indicators [14]. In particular the main point in favour is the capacity to convoy complex information in a unique measure which can be used in decision making. Today, exist many different types of composite indicators (say on competitiveness, innovation and so on) which are used in order to enhance the public debate on important issues

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and the policy-making related to these problems [14]. The composite indicators are considered very useful in policy analysis and in policy communication [14] in order allow them to synthetize quickly complex concepts. In particular the composite indicators are considered useful in order to measure multidimensional and complex phenomena and comparing different statistical units as countries, regions and so on. It is important to note that is more simple in various fields to consider the composite indicators than analyzing the data structure of the different indicators in order to make decisions [19, 14]. At the same time there is a risk to misinterprate the composite indicators. In general a composite indicator start from different measures on a single area (the statistical unit) [14]. In this sense these measures can derive another one which can be used on benchmarking and in monitoring the different performances of the statistical units (for example the regions or countries). The usefulness of a composite indicator as statistical construct is on the fact that ideally the composite indicator needs to measure different and more complex concepts than the simple indicators [14, 1]. In fact the general aim of the composite indicators is measuring phenomena which are not simple to be measured. In this way we consider different indicators in order to measure the phenomenon. A composite indicator at the end can be seen as a model in a sense of mathematical model where different inputs can participates to the outputs sometimes in a nonlinear way [13, 14]. In this context we need explicitly to consider a sensitivity analysis for our model [19, 18]. In particular we have many possible outputs where a typical problem in the composite indicator construction is the subjectivity of the operation. In fact there are many choices in general. These choices that must be performed can lead to different results [14, 3, 19]. However there is a problem of robustness, accuracy and reliability related to the composite indicators [18, 4]. In this sense the actual use of the composite indicators and the proliferation of different measures used in policy making call for new approaches in order to improve accuracy and reliability of the composite indicators.

2 Composite indicator construction

Various phases can be considered in building composite indicators. A review of the techniques used on building composite indicators is on [14, 19, 4]. A theoretical framework on the statistical and mathematical properties on the construction of the composite indicators is also proposed by [1]. These different analyses need to be well documented and explained when a composite indicator is constructed. In this sense it is important to document the different assumptions which are done in the construction of the composite indicators [19]. These assumptions can have a relevant impact on the outputs [14]. In this sense the construction of a composite indicator is very similar to a model construction therefore the different assumptions made need to be considered in a clear way [14, 17]. However it is very important to consider the different phases on the construction of a composite indicator. These phases can be defined in this way [14, 19, 4, 1]:

- Theoretical framework
- Data selection
- Treatment of the missing data
- Multivariate Analysis
- Normalization
- Weighting and aggregation
- Robustness and sensitivity
- Repeatibility of the composite indicators ("back to the initial data" [14])
- Analysis of the linkages with other variables
- Visualization and presentation

These steps are useful in order to obtain a set of outputs (or scores) as composite indicators [14, 13, 1]. In particular the authors [14] emphasize the role of the multivariate analysis to avoid the lack of information in a construction of a composite indicator with variables. The adequacy of the constructs obtained [1] can be considered in this sense in order to avoid structures with variables are redundant. In this sense the multivariate techniques are used to explore the data structure. A strategy which is considered is to apply a principal component analysis (in order to detect the relevant variables) and then a clustering procedure sequentially in order to detect significant groups of the data [14, 6]. Now we see in practice the construction of a composite indicator. Following [17, 1], in order to obtain the composite indicator Y_u for a given statistical unit u where the aggregation can be done by considering the normalized subindicators $I_{q,u}$ with at the same time the defined weights w_q. The weights define the importance of each subindicator. As well we have chosen a k specific combination between the set of the possible different assumptions in the construction of the composite indicator Y^c. So we have in most of cases [14, 17, 4]:

$$Y_u^c = \sum_{q=1}^{Q} I_{q,u} w_q \tag{1}$$

With $c = 1 \dots C$ and $0 \leq w_q \leq 1$ and $\sum_{q=1}^{Q} w_q = 1$. There are relevant cases in which can be considered a different aggregation function [14], the geometric one:

$$Y_u^c = \prod_{q=1}^{Q} (w_q I_{q,u})^{1/Q} \tag{2}$$

where as well in this case $c = 1 \dots C$ and $0 \leq w_q \leq 1$ and $\sum_{q=1}^{Q} w_q = 1$

In this sense various authors [14, 1, 4] discuss the different aggregation function which can be used in building composite indicators. For a complete review of the different methodologies used in literature see [14]. Two used procedures in the normalization process of the variables can be the distance from the best and worst performers [17, 4]:

$$I_{q,u} = \frac{x_{q,u} - min(x_q)}{range(x_q)} \tag{3}$$

where $x_{q,u}$ means that each country u is characterized by the subindicator x_q. It is possible to consider also the standard deviation from the mean [4, 17]:

$$I_{q,u} = \frac{x_{q,u} - mean(x_q)}{std(x_q)} \tag{4}$$

The rationale in using these normalizations is to uniforming the different scale of measure of the different variables used in the construction of the composite indicator [14, 17, 4]. Then it is necessary to decide the weighting of the indicators which is the most critical point to solve [17, 14]. In fact the different weighting can have a strong impact on the final outcomes [4]. Various ways of deciding the weights are proposed in literature and can be performed differently [14, 4]. The most simple approach is to weight equally all the different indicators. In this sense in the indicator we typically have:

$$w_0 = w_1 = \cdots = w_q \tag{5}$$

Weighting scheme chosen can be related to the importance of each indicator to consider. Different procedures in order to decide the different weights to adopt was proposed [14, 16].

3 Checking robustness of the composite indicators

Every composite indicator can be obtained by considering different choices related for example to the aggregation considered or the weighting scheme. Sometimes these choices are subjective, require attention and can be discussed [14, 19]. However there is required usually a phase in which alternative approaches are considered in order to assess the different uncertainties which are occurred in the construction of the composite indicator. At the same time are assessed the subjective choices and analyzed the impact of these choices as well [14]. In particular there are two approaches: uncertainty analysis and sensitivity analysis [14]. There are differences on the uncertainty analysis and the sensitivity analysis which are described on [14, 17]. Here we consider explicitly the uncertainty analysis because it is the most used approach in this context [17]. Following [17] it is possible to use the difference between two composite indicators on two statistical units A and B:

$$D_{A,B} = \sum_{q=1}^{Q} (I_{q,A} - I_{q,B}) w_q. \tag{6}$$

In particular the ranks are used in order to analyze the differences between different assumptions considered. The interval is related to the different results in ranking and is possible to obtain. Following as well [17] we can have:

$$\overline{R}_S = \frac{1}{M}\sum_{u=1}^{U} |rank_{ref}(Y_u) - rank(Y_u)| \tag{7}$$

The results of the equations 6 and 7 can confirm the results related to the single composite indicators and their ranks. On the contrary where there are big differences and results it could be necessary to reconsider the analysis [14]. In this sense we want to investigate about Y_u^c in order to assess the differences related to the different assumptions k. The idea is that we build interval data [10] by considering the different assumptions k in order to test the robustness of the results [14]. This idea is based on the concept of sensitivity analysis [20].

4 Using Interval Composite Indicators

The motivations to use intervals and interval data in the analysis of the composite indicators can be the close relationship between intervals and sensitivity analysis [20]. In particular in this sense interval statistics can be used in the case the data can have a specific point estimate and can be characterized by relevant and reliable ranges [10]. So we start from the use of the different assumptions on k and we apply different variations to obtain a different value for the same composite indicator $Y_u^{c,k}$. Then we collect the data by a different statistical unit and we obtain the interval. The interval allows to take into account the different variations which could happen by considering different assumptions k. If we consider only a data for the interval (for example a mean of the different observations we can have a loss of information due to the data aggregation [2]). In this sense we are able to compare the different data obtained and the different intervals by considering the centre, the range, the minima and the maxima. For the computation related to the centre and the radius [5].

4.1 Building Interval Composite Indicators

There are relevant cases which data show relevant problems as uncertainty and imprecise measuring and they are particularly complex in this sense and it is usually necessary to consider some alternative measures. In this sense we use the interval data. Interval data are particularly useful to represent these data by considering the different assumptions. A relevant problem is the robustness of the composite indicators in this sense and we have to do some types of sensitivity analysis. We can have different results from different methods which give different composites indicators, so we can have a set of different composite by condering different k assumptions with $k = 1,2,\dots K$ [15, 5]:

$$Y_k^c, Y_k^c, \dots, Y_K^c \tag{8}$$

By considering all the assumptions of the composite indicators Y_k^c, we can define the obtained interval composite indicator c in this way:

$$I[Y]^c = [\underline{Y}_k^c, \overline{Y}_k^c] \tag{9}$$

Where we have different composite indicators $c = 1 \ldots C$. So we can have for each different intervals one for each different composite indicator c:

$$[\underline{Y_k^1}, \overline{Y_k^1}], [\underline{Y_k^2}, \overline{Y_k^2}], \ldots, [\underline{Y_k^C}, \overline{Y_k^C}] \tag{10}$$

where $c = 1 \ldots C$. The original composite indicator (that we have computed originally and can be the starting point of the robustness analysis) can be denoted Y_{k*}^c. At the same time $\underline{Y_k}$ denote the lower bound where as well the $\overline{Y_k}$ denote the upper bound. The intervals can be defined as:

$$I[Y] = [\underline{Y}, \overline{Y}] = \{Y \in \mathbb{R} : \underline{Y} \leq Y \leq \overline{Y}\} \tag{11}$$

.

In this case the case in which $\underline{Y} = \overline{Y}$ correspond to a real number also defined a scalar [10]. However $I[Y]$ is defined a tiny interval [15] given $I[Y] \subset \mathbb{R}$ if $\underline{Y} = \overline{Y}$. Two intervals $I[Y]^{c'}$ and also $I[Y]^{c''}$ in $\mathbb{R}$ are equals if: $I[Y]^{c'}$ and $I[Y]^{c''} \rightarrow \{\underline{Y^{c'}} = \underline{Y^{c''}}, \overline{Y^{c'}} = \overline{Y^{c''}}\}$ [15, 5]. The intervals shows some relevant characteristics which can be considered in applications: the radii and the midpoints.

4.2 Interval Radii and Midpoints

In order to analyze the different results we can compare the different interval data which are obtained. In particular the interval data show relevant features which can be considered. Following [15] these features are the center (also defined midpoint) and the radii of the interval. We can obtain the center:

$$Y_{center,k}^c = \frac{1}{2}(\underline{Y}_k^c + \overline{Y}_k^c) \tag{12}$$

And the radius of the interval:

$$Y_{radius,k}^c = \frac{1}{2}(\overline{Y}_k^c - \underline{Y}_k^c) \tag{13}$$

The center correspond to a location measure considering all the different composite indicators computed by considering different set of assumptions. The radius as well can be interpreted in this way, where the length span (the difference between upper and lower bound) represent a variability measure between the different composite indicators based on the various assumptions.

4.3 Applying Interval Arithmetic

We can consider some relevant operations between the identified intervals. Algebraic operations are possible comprehending the sum, the subtraction, the multiplication and the division [9, 15]. In particular we have: $I[Y]_k^{c'} = \{\underline{Y_k^{c'}}, \overline{Y_k^{c'}}\}$ and $I[Y]_k^{c''} = \{\underline{Y_k^{c''}}, \overline{Y_k^{c''}}\}$ then:

$$I[Y]_k^{c'} \text{ op } I[Y]_k^{c''} = \{Y_k^{c'} \text{ op } Y_k^{c''} | Y_k^{c'} \in I[Y]_k^{c'} \text{ and } Y_k^{c''} \in I[Y]_k^{c''}\} \tag{14}$$

The symbol op denote the for operations: $op \in \{+,-,\times,:\}$. We can have as arithmetical rules between different intervals [10]:

$$\begin{aligned}
&I[Y]_k^{c'} + I[Y]_k^{c''} = [\underline{Y_k^{c'}}, \overline{Y_k^{c'}}] + [\underline{Y_k^{c''}}, \overline{Y_k^{c''}} = [\underline{Y_k^{c'}} + \underline{Y_k^{c''}}, \overline{Y_k^{c'}} + \overline{Y_k^{c''}}]\\
&I[Y]_k^{c'} - I[Y]_k^{c''} = [\underline{Y_k^{c'}}, \overline{Y_k^{c'}}] - [\underline{Y_k^{c''}}, \overline{Y_k^{c''}} = [\underline{Y_k^{c'}} - \overline{Y_k^{c''}}, \overline{Y_k^{c'}} - \underline{Y_k^{c''}}]\\
&I[Y]_k^{c'} \times I[Y]_k^{c''} = [\underline{Y_k^{c'}}, \overline{Y_k^{c'}}] \times [\underline{Y_k^{c''}}, \overline{Y_k^{c''}}] = min(\underline{Y_k^{c'} Y_k^{c''}}, \overline{Y_k^{c'} Y_k^{c''}}, \underline{Y_k^{c'}} \overline{Y_k^{c''}}, \overline{Y_k^{c'}}, \underline{Y_k^{c''}}),\\
&max(\underline{Y_k^{c'} Y_k^{c''}}, \overline{Y_k^{c'} Y_k^{c''}}, \underline{Y_k^{c'}} \overline{Y_k^{c''}}, \overline{Y_k^{c'}}, \underline{Y_k^{c''}})\\
&I[Y]_k^{c'} \div I[Y]_k^{c''} = [\underline{Y_k^{c'}}, \overline{Y_k^{c'}}] \div [\underline{Y_k^{c''}}, \overline{Y_k^{c''}}] = [\underline{Y_k^{c'}}, \overline{Y_k^{c'}}] \times [1/\overline{Y_k^{c''}},\ 1/\underline{Y_k^{c''}}], \text{ where } 0 \notin Y_k^{c''}]
\end{aligned} \tag{15}$$

In this sense we can analyze statistically the different intervals obtained [10, 5]. Particularly relevant in applications is to consider the mean of the intervals [15, 5]. In this sense we can have:

$$I[\overline{Y}]_k^c = \frac{1}{N} \sum_{i=1}^{N} I[Y]_k^c \tag{16}$$

where we can have: $I[\overline{Y}]_k^c \subset \mathbb{R}\ c\ \forall \in \{1,\ldots,N\}$
Now we consider the way to compare different composite indicators.

4.4 Comparing Interval Composite Indicators

Ordering intervals is a relevant problem in decision making. There can be considered various alternatives in order to compare the different intervals. For a review of the methodologies related to the ordering of intervals see [8]. Following [12] we can have two distinct cases: disjoint intervals and no disjoint intervals. In the first case of the disjoint intervals we have an example on figure 1.

The case of the disjoint intervals is straightforward and can be considered if the second interval $I[Y]_k^{c''}$ is higher than the first one based on $I[Y]_k^{c'}$ [12]. In fact the $I[Y]_k^{c'}$ can be considered strictly lower than $I[Y]_k^{c''}$. In the second case we can have

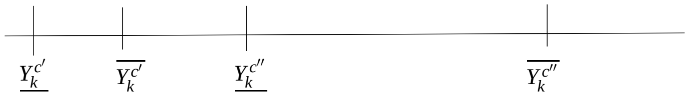

Fig. 1 Disjoint Intervals

disjoint intervals and we can see as well an example in the fig. 2. We have to consider three different situations:

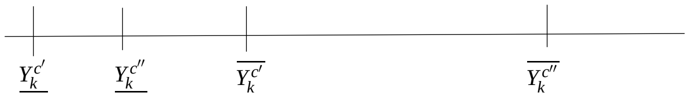

Fig. 2 No Disjoint Intervals

In particular we can consider the two cases of disjoint and no disjoint intervals. In the case of disjoint intervals we can order the different intervals in this way:

- The upper bound $\overline{Y_k^c}$
- The lower bound $\underline{Y_k^c}$
- The centre (equation 12) or the mean (equation 16)
- The span length $\overline{Y_k^c} - \underline{Y_k^c}$

In this sense the interval data related to the different assumptions k of the composite indicators can be ranked by considering their centre [12, 11, 7] and also [8]. In particular the centre can be used in order to compare the different intervals by a location measure where the span length can be used in order to compare the variability of two or more intervals. Clearly it is possible to consider the original value for the composite indicator obtained at the start of the analysis Y_{k*}^c and considering this measure for the ranking (and this measure is normally used on all the actual comparison and rankings and is subjected to uncertainty analysis and sensitivity analysis). An important case defined in [8] is the case of equal centers and different radii for two intervals. For example we can have: $I[Y]_k^{c'} = [0,7]$ and $I[Y]_k^{c''} = [3,4]$. In this case we can observe that the two interval composite indicators have the same centre and a different midpoint or radius. We can have in this sense [7, 8]:

$$I[Y]_k^{c'} \prec= I[Y]_k^{c''} \begin{cases} Y_{center,k}^{c'} < Y_{center,k}^{c''} & \text{where } Y_{center,k}^{c'} \neq Y_{center,k}^{c''} \\ Y_{radius,k}^{c'} \geq Y_{radius,k}^{c''} & \text{where } Y_{radius,k}^{c'} = Y_{radius,k}^{c''} \end{cases} \tag{17}$$

Now we consider the correct way to interpreting the different results which can be obtained.

5 Explaining and interpreting the Intervals

We have performed a simulated example in building a composite indicator in which we have considered a single source of uncertainty by considering different sub-indicators [17] in a composite indicator. We obtain a ranking of the intervals and we can order the same intervals by considering the centers. The algorithms for the methods and for the simulation was written on R language. We consider here the way in which can be interpreted the outputs of the interval composite indicators. In this sense we can start from the original value of the composite indicator Y^c_{k*} this can be considered the baseline scenario (in particular it could be considered [4] in order to give an example of composite indicator construction in practice). A ranking on the different statistical units considered u can be performed directly considering the baseline scenario considered then in order to perform uncertainty analysis we build the different composite indicators using other assumptions and we obtain different composite indicators which are part of the interval as well. Finally we are able to compute the centers, the mid points and the the length span (defining the uncertainty). In this sense we are able to compare the rankings related to the different results we can obtain for the interval based composite indicator. It is possible to follow [21] in order to interpret correctly the results we can obtain from the interval analysis. In particular there are two interpretations of the intervals which could be used [21, 10]: the equiprobability model and the uncertainty on the data. In all cases the centre of the interval give us the expected values of the composite indicator considering the different assumptions where the length span is related to the uncertainty of the different results which can be obtained. In order to consider the different features of the intervals as the upper, the lower bounds, the centers or the length span it is possible to construct the rankings of the intervals.

6 Conclusions

In this work we have proposed a new different approach in the construction of the composite indicators. In particular this new approach is based on the uncertainty analysis with the aim of analysing the robustness of the different results making it possible to obtain from changing the intial assumptions on the construction of the composite indicator. The results seem to be interesting because the intervals tend to endogenize directly the differences in values of the built composite indicators. In this case it is possible to improve the communication because it is possible to show directly on the final results how results change in scores by considering different assumptions. It is clearly possible as well to keep the original information (the baseline value of the composite indicator) because it is possible to consider the original values of the composite indicators and also the centres of the intervals. Future development can be addressed to propose applications of these approaches in various fields.

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