



Composite Indices Construction: The Performance Interval Approach

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Abstract

In the last years, there has been a growing interest in composite indices, whether they be social, socio-economic or environmental indices. In this paper, we propose a new approach to the composite indices construction which consists in computing an interval of possible values, for each statistical unit, rather than a single value. The interval is called ‘performance interval’ and it is constructed depending on the level of compensability of individual indicators. As an example of application, we considered a set of indicators of well-being in Italy and we constructed the performance intervals for the Italian Regions. Finally, we compared the midpoint of the performance intervals with the geometric mean, a classic partially compensatory aggregation function.

Keywords Data aggregation · Full-compensability · Non-compensability

1 Introduction

Composite indices have been increasingly recognized as a useful tool for measuring complex and multidimensional phenomena, such as development, poverty, quality of life, well-being, globalization, competitiveness, freedom, and so on. In particular, they allow to assess or rank the performance of a set of statistical units (e.g., countries or geographical areas) based on a set of individual indicators that have no common meaningful unit of measurement or obvious way to be weighed (e.g., “Life expectancy at birth” and “Gross national income per capita”), in order to make comparisons, benchmarking, policy analysis and public communication (OECD 2008).

Technically, a composite index is a mathematical combination (or aggregation as it is termed) of a set of indicators that represent the different dimensions of a phenomenon to be measured (Saisana and Tarantola 2002). A typical example of composite index is the United Nations’ *Human Development Index* (HDI) that summarizes the average achievement in three key dimensions of human development: health, knowledge and standard

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of living. The HDI is the geometric mean of normalized indicators for each of the three dimensions (UNDP 2010, 2018).

From social aspects to governance and the environment, the number of composite indices is constantly growing at a rapid pace (Greco et al. 2019). Bandura (2011) has provided a review of over 400 official composite indices for ranking or assessing country performance according to some economic, political, social or environmental measure.

However, the idea of summarizing a complex phenomenon into a single number is not straightforward, as it involves both theoretical and methodological assumptions that need to be assessed carefully to avoid producing results of dubious analytic rigour (Saisana et al. 2005). The main steps to follow are (Mazziotta and Pareto 2017): (1) Defining the phenomenon to be measured, (2) Selecting a set of individual indicators, (3) Normalizing¹ the individual indicators, (4) Aggregating the normalized indicators, and (5) Validating the composite index. Each of these stages requires subjective choices that can be questionable. Therefore, composite indices can send misleading messages if they are poorly constructed or misinterpreted.

One of the major criticisms of composite indices is that their simple ‘big picture’ results may invite users (especially policy-makers) to draw simplistic analytical or policy conclusions (OECD 2008). In this paper, we propose to overcome the problem of calculating a single number, by constructing an interval of potential values of the composite index. The interval is called ‘performance interval’ and it is constructed depending on the level of compensability of individual indicators.

In Sect. 2, the difference between compensatory e non-compensatory approach in composite indices construction is discussed. In Sect. 3, the power mean of order r and its relation with the assumption on the degree of compensability or substitutability of the individual indicators is examined. In Sect. 4, the method for constructing the ‘performance interval’ is presented; whereas in Sect. 5 an application to real data is shown by using a number of individual indicators of well-being for Italian regions, in 2017. Finally, some comments about the results and their graphical representation are given.

2 Compensatory and Non-compensatory Approach

A fundamental issue concerning composite index construction is the degree of compensability or substitutability of the individual indicators.

The components of a composite index are called ‘substitutable’ if a deficit in one component may be compensated by a surplus in another (e.g., a low value of “Proportion of people who have participated in religious or spiritual activities” can be offset by a high value of “Proportion of people who have participated in meetings of cultural or recreational associations” and vice versa). Similarly, the components of a composite index are called ‘non-substitutable’ if a compensation among them is not allowed (e.g., a low value of “Life expectancy at birth” cannot be offset by a high value of “Gross national income per capita” and vice versa).² Thus we can define an aggregation approach as ‘compensatory’ or

¹ Normalization step aims to make the indicators comparable, because they often have different measurement units and ranges (Mazziotta and Pareto 2017).

² Note that compensability/non-compensability does not imply dependence/independence and vice versa. For example, “Hospital beds (per 1000 people)” and “Hospital doctors (per 1000 people)” are two dependent (positively correlated) indicators but they are non-substitutable, because a deficit in beds cannot be offset by a surplus in doctors and vice versa (Mazziotta and Pareto 2016).

'non-compensatory' depending on whether it permits compensability or not (Casadio Tarabusi and Guarini 2013). An in-between approach based on an 'imperfect substitutability' across all components of a composite index is called 'partially compensatory'.

Compensability is closely related with the concept of unbalance, i.e., a disequilibrium among the indicators that are used to build the composite index. In any composite index each dimension is introduced to represent a relevant aspect of the phenomenon considered, therefore a measure of unbalance among dimensions may help the overall understanding of the phenomenon. In a non-compensatory or partially compensatory approach, all the dimensions of the phenomenon must be balanced and an aggregation function that takes unbalance into account, in terms of penalization, is often used.

A compensatory approach involves the use of additive methods, such as the arithmetic mean. A partially compensatory or non-compensatory approach requires the use of non-linear functions, such as the geometric mean (OECD 2008) or the minimum (Casadio Tarabusi and Guarini 2013).

3 The Power Mean of Order r

As we know, the most common aggregation function for constructing a composite index is the summation of weighted and normalized individual indicators (OECD 2008). An additive aggregation function allows assessment of the marginal contribution of each individual indicator separately. These marginal contributions can then be added together to yield a total value. However, an undesirable feature of additive aggregations is the implied full compensability, such that poor performance in some indicators can be compensated for by sufficiently high values in other indicators (perfect substitutability).

A widely used alternative is the geometric aggregation (Zhou et al. 2010), where a multiplicative function is used. This aggregation function allows a partial compensability, so that an increase in the most deprived indicator will have a higher impact on the composite index (imperfect substitutability). Such a choice is advisable whenever a reasonable achievement in any of the individual indicators is considered to be crucial for overall performance (Chiappero-Martinetti and von Jacobi 2012).

Additive and multiplicative aggregation functions can be seen as special cases of a generalized mean or power mean of order r . Given the normalized data matrix $\mathbf{Y}_{n,m} = \{y_{ij}\}$, with n rows (statistical units) and m columns (normalized indicators), the power mean of order r , for unit i , is defined as follows:

$$M_i^r = \left(\sum_{j=1}^m y_{ij}^r w_j \right)^{\frac{1}{r}}$$

where w_j is the weight of indicator j ($0 < w_j < 1$) with $\sum_{j=1}^m w_j = 1$.

For $r = 1$, we have the additive function, and for $r \rightarrow 0$, we have the multiplicative one.

In Table 1 are reported main special cases of the power mean of order r . The table also provides the type of approach and the features (intensity and direction) of the penalization for unbalanced values.

If the composite index to be constructed is 'positive', i.e., increasing values of the index correspond to an improvement of the phenomenon (e.g., socio-economic development), a downward penalization must be used. On the contrary, if the composite index is 'negative',

Table 1 Special cases of the power mean of order r

Order	Formula	Aggregation function	Approach	Penalization	
				Intensity	Direction
$r \rightarrow -\infty$	$M_i^{-\infty} = \min_j(y_{ij})$	Minimum	Non-compensatory	Maximum	Downward
$r = -1$	$M_i^{-1} = \left(\sum_{j=1}^m \frac{w_j}{y_{ij}} \right)^{-1}$	Harmonic mean	Partially compensatory	High	Downward
$r \rightarrow 0$	$M_i^0 = \prod_{j=1}^m y_{ij}^{w_j}$	Geometric mean	Partially compensatory	Low	Downward
$r = 1$	$M_i^1 = \sum_{j=1}^m y_{ij} w_j$	Arithmetic mean	Compensatory	None	–
$r = 2$	$M_i^2 = \left(\sum_{j=1}^m y_{ij}^2 w_j \right)^{\frac{1}{2}}$	Quadratic mean	Partially compensatory	Low	Upward
$r = 3$	$M_i^3 = \left(\sum_{j=1}^m y_{ij}^3 w_j \right)^{\frac{1}{3}}$	Cubic mean	Partially compensatory	High	Upward
$r \rightarrow +\infty$	$M_i^{+\infty} = \max_j(y_{ij})$	Maximum	Non-compensatory	Maximum	Upward

i.e., increasing values of the index correspond to a worsening of the phenomenon (e.g., poverty), an upward penalization must be used. In any cases, an unbalance among indicators values will have a negative effect on the value of the index.³

Due to the penalization (upward or downward), we have:

$$M_i^{-\infty} \leq \dots \leq M_i^{-1} \leq M_i^0 \leq M_i^1 \leq M_i^2 \leq M_i^3 \leq \dots \leq M_i^{+\infty} \tag{1}$$

and the means are equal if and only if $y_{ij} = y_{ik}$ ($j \neq k$).

4 The Performance Interval Approach

Based on the inequalities of the power means, it is possible to construct an interval of possible values, for each statistical unit, rather than a single value. The interval is called ‘performance interval’ and it is constructed depending on the level of compensability of individual indicators.

It is worth noting that the performance interval is not a probabilistic interval, such as the ‘confidence interval’, since the composite index is not a point estimate computed from a well-defined sample.⁴

The performance interval generates a lower and upper bound for the composite index: one bound corresponds to the hypothesis of full-compensability of individual indicators

³ Note that a simple non-compensatory approach uses the minimum (maximum) value of the normalized indicators so that the other values cannot increase (decrease) the value of the index. This function realizes the maximum penalization for unbalanced values of the indicators (Casadio Tarabusi and Guarini 2013).

⁴ A composite index can summarize values of different type (e.g., sample estimates, model-based estimates and census estimates).

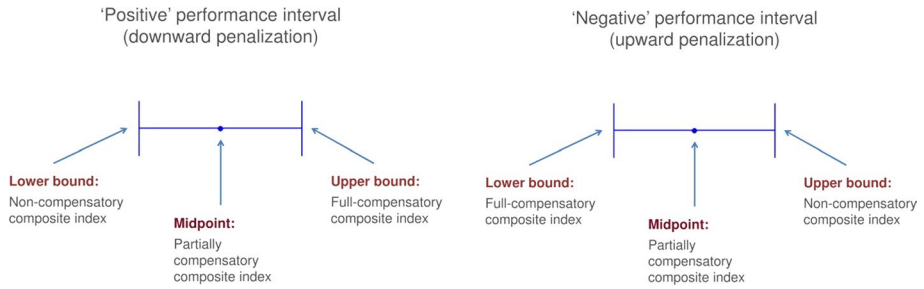


Fig. 1 Performance interval construction

(full compensatory composite index), whereas the other bound corresponds to the hypothesis of non-compensability of individual indicators (non-compensatory composite index). From this point of view, the centre of the interval (midpoint) may be regarded as the value of the composite index under the hypothesis of partial compensability (partially compensatory composite index).

Two different performance intervals can be defined, for unit *i*, depending on the phenomenon to be measured:

(a) ‘Positive’ performance interval

$$\left(\min_j(y_{ij}); \frac{1}{m} \sum_{j=1}^m y_{ij}w_j \right)$$

where the upper bound corresponds to the hypothesis of full-compensability of individual indicators (arithmetic mean), whereas the lower bound corresponds to the hypothesis of non-compensability of individual indicators (minimum).

(b) ‘Negative’ performance interval

$$\left(\frac{1}{m} \sum_{j=1}^m y_{ij}w_j; \max_j(y_{ij}) \right)$$

where the lower bound corresponds to the hypothesis of full-compensability of individual indicators (arithmetic mean), whereas the upper bound corresponds to the hypothesis of non-compensability of individual indicators (maximum).

A ‘positive’ performance interval must be used to apply a downward penalization; whereas a ‘negative’ performance interval must be used to apply an upward penalization. In Fig. 1, the two types of intervals are displayed.

Note that the length of the interval can be considered as a measure of imbalance of normalized indicators. If normalized indicators are perfectly balanced, the performance interval reduces to a single point, and the value of the composite index is independent of any hypothesis on the level of compensability of individual indicators. The greater the length of the interval, the greater the imbalance of normalized indicators and the larger the difference between the value of the full-compensatory composite index and the value of the non-compensatory composite index.

Table 2 Individual indicators of well-being in the Italian regions—year 2017

Regions	Income per capita (euro)	Life expectation (years)	Graduates aged 30–34 (%)	Unemployment rate (%)	Separate waste collection (%)
Piemonte	20,727	82.5	26.4	9.1	59.3
Valle d'Aosta	20,901	82.0	25.2	7.8	61.1
Liguria	21,639	82.7	23.7	9.5	48.8
Lombardia	22,419	83.3	33.7	6.4	69.6
Trentino Alto Adige	23,193	83.8	29.1	4.4	72.0
Veneto	20,350	83.4	27.6	6.3	73.6
Friuli Venezia Giulia	20,562	83.0	28.7	6.7	65.5
Emilia Romagna	22,463	83.2	29.9	6.6	63.8
Toscana	20,275	83.3	28.3	8.6	53.9
Umbria	18,038	83.3	29.7	10.6	61.7
Marche	18,722	83.3	33.0	10.6	63.2
Lazio	19,366	82.5	30.1	10.7	45.5
Abruzzo	16,284	82.6	25.8	11.7	56.0
Molise	14,416	82.3	26.1	14.6	30.7
Campania	13,153	81.1	21.4	20.9	52.8
Puglia	13,932	82.7	22.2	18.9	40.4
Basilicata	13,483	82.3	29.2	12.8	45.3
Calabria	12,656	82.1	20.7	21.6	39.7
Sicilia	13,286	81.6	19.1	21.5	21.7
Sardegna	15,240	82.8	23.6	17.0	63.1

The performance interval is independent of the data normalization. Therefore, individual indicators can be normalized by various method, such as ranking, re-scaling (or Min–Max), standardization (or *z*-scores) and ‘distance’ from a reference (or indicization).

5 An Application to Well-Being Data

In this Section, an application of the performance interval approach to a set of indicators of well-being for Italian regions, in 2017, is presented (Istat 2018).

The original data matrix is reported in Table 2, where five basic indicators are considered: “Income per capita (euro)”, “Life expectation (years)”, “Graduates aged 30–34 (%)”, “Unemployment rate (%)” and “Separate waste collection (%)”. All individual indicators have positive polarity,⁵ except “Unemployment rate (%)” which has negative polarity.

The aim of the work is to construct a performance interval of well-being for each Italian region, rather than a single composite index. In the hypothesis of partial substitutability of individual indicators, the midpoint of the interval may be regarded as the value of a partially compensatory composite index.

⁵ The polarity of an individual indicator is the sign of the relation between the indicator and the phenomenon to be measured. When a composite index must be constructed, all the individual indicators must have positive polarity, so it is necessary to ‘invert’ the sign of the indicators with negative polarity (Mazziotta and Pareto 2017).

Table 3 Normalized indicators of well-being in the Italian regions—year 2017

Regions	Income per capita (euro)	Life expectation (years)	Graduates aged 30–34 (%)	Unemployment rate (%)	Separate waste collection (%)
Piemonte	107.6	97.1	99.3	105.1	103.6
Valle d'Aosta	108.1	89.4	96.2	107.5	105.0
Liguria	110.1	100.2	92.4	104.3	95.9
Lombardia	112.3	109.3	118.0	110.1	111.3
Trentino Alto Adige	114.5	117.0	106.2	113.9	113.1
Veneto	106.5	110.9	102.4	110.3	114.2
Friuli Venezia Giulia	107.1	104.8	105.2	109.6	108.2
Emilia Romagna	112.5	107.8	108.3	109.8	107.0
Toscana	106.3	109.3	104.2	106.0	99.6
Umbria	100.0	109.3	107.8	102.3	105.4
Marche	101.9	109.3	116.2	102.3	106.5
Lazio	103.7	97.1	108.8	102.1	93.4
Abruzzo	95.0	98.6	97.8	100.2	101.2
Molise	89.7	94.0	98.5	94.8	82.4
Campania	86.1	75.6	86.4	83.0	98.8
Puglia	88.3	100.2	88.5	86.7	89.6
Basilicata	87.1	94.0	106.5	98.2	93.3
Calabria	84.7	91.0	84.7	81.7	89.1
Sicilia	86.5	83.3	80.5	81.8	75.8
Sardegna	92.0	101.7	92.1	90.3	106.5

A positive performance interval is computed, because the composite index of well-being is 'positive', i.e., increasing values of the index correspond to positive variations of well-being. Thus, adopting a negative penalty produces index values lower than the arithmetic mean, with the largest changes occurring in regions with uneven well-being across dimensions.

The normalized data matrix is reported in Table 3, where individual indicators are normalized as follows:

$$y_{ij} = 100 + \frac{(x_{ij} - M_{x_j})}{S_{x_j}} 10 \quad \text{if indicator } j \text{ has positive polarity;}$$

$$y_{ij} = 100 - \frac{(x_{ij} - M_{x_j})}{S_{x_j}} 10 \quad \text{if indicator } j \text{ has negative polarity;}$$

where x_{ij} is the original value of indicator j for unit i , M_{x_j} and S_{x_j} are, respectively, the mean and standard deviation of indicator j . So, all normalized indicators have a mean of 100 and a standard deviation of 10.

All indicators were assigned equal weights, so that $w_j=0.2$ ($j=1, \dots, 5$). Table 4 shows the lower (LB) and upper (UB) bound for the composite index of well-being: LB represents the non-compensatory composite index of well-being, whereas UB represents the full compensatory composite index of well-being. The table also provides the midpoint of the performance interval and the geometric mean, two possible partially compensatory composite

Table 4 Composite Indices of well-being in the Italian regions—Year 2017

Regions	Performance Interval		Composite index		Rank		
	LB	UB	Midpoint	Geometric Mean	Midpoint	Geometric Mean	Midpoint-Geometric mean
Piemonte	97.1	102.5	99.8	102.5	9.0	9.0	0
Valle d'Aosta	89.4	101.2	95.3	101.0	13.0	10.0	3
Liguria	92.4	100.6	96.5	100.4	12.0	12.0	0
Lombardia	109.3	112.2	110.8	112.2	1.0	2.0	-1
Trentino Alto Adige	106.2	112.9	109.6	112.9	2.0	1.0	1
Veneto	102.4	108.9	105.6	108.8	5.0	4.0	1
Friuli Venezia Giulia	104.8	107.0	105.9	107.0	4.0	6.0	-2
Emilia Romagna	107.0	109.1	108.0	109.0	3.0	3.0	0
Toscana	99.6	105.1	102.4	105.0	8.0	7.0	1
Umbria	100.0	105.0	102.5	104.9	7.0	8.0	-1
Marche	101.9	107.3	104.6	107.1	6.0	5.0	1
Lazio	93.4	101.0	97.2	100.9	10.0	11.0	-1
Abruzzo	95.0	98.6	96.8	98.5	11.0	13.0	-2
Molise	82.4	91.9	87.2	91.7	17.0	16.0	1
Campania	75.6	86.0	80.8	85.7	19.0	19.0	0
Puglia	86.7	90.7	88.7	90.5	16.0	17.0	-1
Basilicata	87.1	95.8	91.4	95.6	15.0	15.0	0
Calabria	81.7	86.2	83.9	86.2	18.0	18.0	0
Sicilia	75.8	81.6	78.7	81.5	20.0	20.0	0
Sardegna	90.3	96.5	93.4	96.3	14.0	14.0	0
Mean absolute difference							0.80
Spearman's rank correlation							0.980

indices. Finally, the rankings according to these two indices are reported and compared by the mean absolute difference of rank and the Spearman's rank correlation.

Overall, the results are concordant and the Spearman rank correlation coefficient between the performance interval midpoint and the geometric mean is $\rho=0.980$, with a mean absolute difference of rank of 0.8 positions. The greatest absolute difference of rank is observed for Valle d'Aosta (3 positions) that is penalized from a low normalized minimum value (see "Life expectation (years)"). Note also that the intensity of the penalization of the midpoint is greater than the penalization of the geometric mean, because of the 'effect' of the minimum on the calculation of the midpoint.⁶

In Fig. 2 are displayed the performance intervals of well-being for the Italian regions in 2017 (midpoints are signed in red). There are a number of points of interest in the chart.

⁶ Often the minimum and maximum are *outliers* that can heavily affect the mean value.

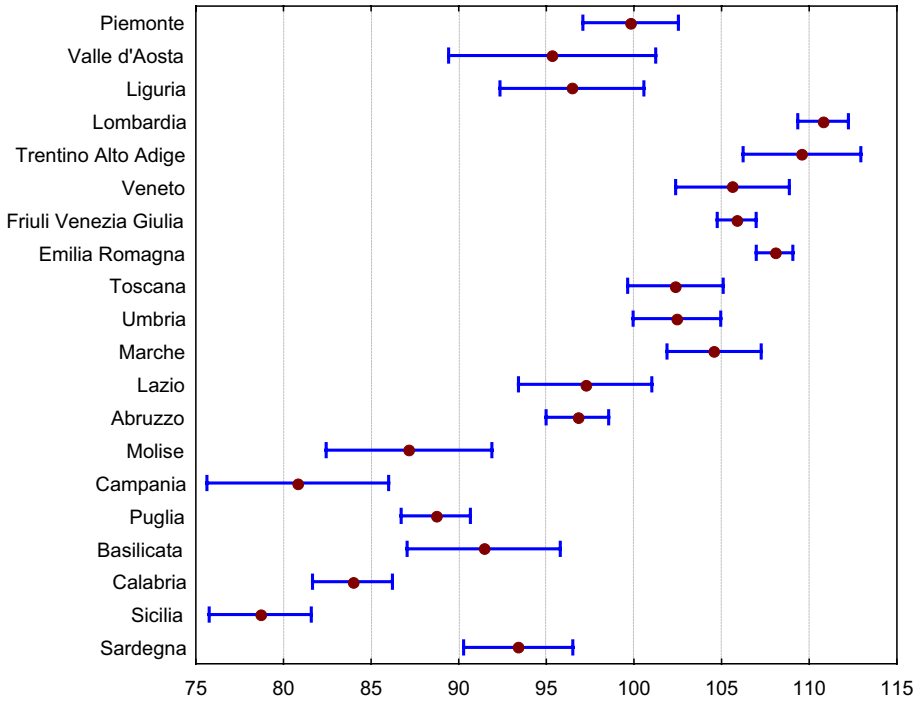


Fig. 2 Performance interval of well-being (year 2017)

Firstly, three different type of rankings are shown: (i) the ‘full-compensatory’ ranking if UB is considered, (ii) the ‘partially-compensatory’ ranking if midpoint is considered, and (iii) the ‘non-compensatory’ ranking if LB is considered.

Secondly, each region has a performance interval of different width. This is due to the different variability (i.e., imbalance of normalized indicators) of the regions.

Thirdly, a region can perform better than another region from a non-compensatory point of view, but it can perform worse from a full compensatory point of view. In this case, the performance interval of the region is contained within a larger performance interval. For example, Liguria has a non-compensatory composite index (i.e., the minimum) greater than Valle d’Aosta, but Valle d’Aosta has a full compensatory composite index (i.e., the arithmetic mean) greater than Liguria.

Another interesting aspect is that if the LB of a region is greater than the UP of another, its performance can be considered better, regardless of the degree of compensability or substitutability of the individual indicators. So, Calabria has a level of well-being greater than Sicilia.

Lastly, the smaller the length of the interval, the more balanced is the performance of a region. In this respect, Emilia Romagna is the region where the best balance among normalized indicators of well-being is achieved.

6 Conclusions

In the literature the debate on the usefulness of composite indices is still very heated. The parts on the field are, on some specific themes, very distant. On the one hand there are the opponents who often even become “Haters”: they claim that it is not possible to reduce the complexity to a single number because the conclusions that derive from it are simplistic and not representative of the multidimensional reality. The haters prefer to analyse the set of individual indicators by claiming that the informational power of the dashboard is irreplaceable. The second faction is made up of the “Lovers” of the composite indices: they are inclined to synthesize anything using very risky models and/or methods. Lovers tend to greatly override the basic rules of composite index construction since the goal to be achieved at any cost is a single number representing the multidimensional phenomenon. The forced search for a methodology that can reduce complexity often generates problems of adaptation between theory and practice: usually the difference between the formative and reflective model is not taken into account and the results could be completely misleading (Mazziotta and Pareto 2019). A third group is constituted by the “Possibilists”: they are researchers who have no qualms about applying the composite indices, rather they are inclined to the synthesis of complex phenomena since they believe that it is appropriate to apply methodologies that facilitate the reading of multidimensional reality. However the Possibilists believe that the composite indices should not be applied in the official statistics since the risk of replacing the consolidated macroeconomic measures is too high and it is not worth the risk. There are obviously other types of researchers who take more nuanced positions among the three described above.

The advantages for constructing a composite index are known to all experts, and they consist mainly of simplicity of the result (the single ranking) and the ease with which it is possible comparing the different units. On the other hand, different aggregation functions will produce different results for the composite index and it will flatten the dynamism of the phenomenon (Alaimo and Maggino 2020). Furthermore, the problem of producing a single number for a complex phenomenon is the defect that accumulates all three categories of researchers mentioned above.

The performance intervals allow for overcoming these problems by providing a result (the range of values) which does not depend on the adopted aggregation function. This makes it possible to avoid an arbitrary choice of the aggregation function and, above all, it has the advantage of producing not a single result. The choice of the level of compensation of the individual indicators is particularly decisive if the ‘horizontal variability’ (Mazziotta and Pareto 2016) of the indicators is high or very high. From a certain point of view, this approach seems to make the composite index resemble an inferential estimate and the performance interval a confidence interval.

This innovative approach makes it possible to include all the composite indices of a statistical unit (geographical area or other) within a defined range in which all the values are included as the compensation level varies. And it is important to point out that all the composite indices are within that range. The researcher can then choose the level of compensation of the individual indicators and obtain a value among all the possible ones.

It seems particularly interesting to study the overlapping of performance intervals from the point of view of both methodological and socio-economic reading of the measured phenomenon. In the case of the application to real data (Sect. 5), the results seem very interesting and deserve to be examined in depth because they draw a “Geography of well-being” in Italy that may vary depending on the choice of the methodology of synthesis. However, the groups that

are created are quite defined and those with a high level do not overlap with those with a low level of well-being.

The approach proposed in the paper seems to satisfy all categories of researchers regarding the construction and use of composite indices; probably it is less usable from a journalistic point of view because the non-scientific information needs clearer and more defined messages so that they can be understood by a vast public that is not used to dealing with statistical-mathematical methodologies. This is not a minor problem since the widespread use of composite indices is also and above all due to journalists who particularly appreciate the ranking of the best and the worst.

The performance intervals are an easy to apply approach that significantly allows the choice of the composite index that best meets the compensation criteria of the individual indicators. Furthermore, it is an approach that overcomes the defect of composite indices to present a single value for each single statistical unit.

It is an attempt to respond not only to the critics of the composite indices but also to those who use them in an inappropriate manner.

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