



Decision support

A new class of composite indicators: The penalized power mean

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ABSTRACT

In this paper we propose a new aggregation method for constructing composite indicators based on a penalization of the power mean. The idea underlying this approach consists in multiplying the power mean by a factor that accounts for the horizontal heterogeneity among indicators while penalizing units with a larger heterogeneity. In line with the minimum loss of information principle, the penalization factor proposed is proven to be linked to the loss of information generated when the indicators are substituted with their power means. As a consequence, the aggregation approach gives rise to the class of penalized power means and the penalized Benefit of the Doubt aggregative approach. Including heterogeneity makes the aggregation approach more suitable for refined rankings. Interestingly, the penalized power mean of order one coincides with the Mazziotta Pareto Index. Some theoretical properties of the penalized power means are proven, thus supporting the Mazziotta Pareto index. An empirical analysis of the Human Development Index in 2019 is presented. Comparisons of the rankings induced by the penalized and non-penalized Benefit of the Doubt and power mean aggregation approaches are shown. There are three main findings: the penalized power means satisfy the properties characterizing weakly monotone aggregation functions; the penalization reduces ranking variations while differentiating units with close means; and the geometric mean provides composite indicators whose ranking is closest to those obtained with power means of different order.

1. Introduction

The construction of composite indicators consists in reducing a multidimensional phenomenon to a one-dimensional phenomenon aggregating the multiple dimensions, namely the indicators, into a single indicator called the composite indicator. The resulting composite indicator, although simpler and easier to interpret and understand, is less informative with respect to the vector of the indicators. That is, the aggregation procedure involves a loss of information. Despite the effort of many authors to develop objective measures of information loss (see, among others, Zhou, Ang, and Poh (2006), Zhou and Ang (2009), Zhou, Fan, and Zhou (2010)), choosing an effective measure is a crucial task and depends on the subjective preference of the decision maker.

A good aggregation should conjugate the contrasting twofold objectives of reducing the dimension of the phenomenon under investigation while generating a reasonable loss of information. The majority of aggregation functions are based on minimizing the loss due to replacing the indicators with the aggregated value. Specifically, the power means are found by choosing the Euclidean distance from the vector of indicators transformed through a Box–Cox function as a penalty (loss) function (for more details we refer to Berger and Casella (1992)). In other words, the power mean can be viewed as the least-squares estimate of the vector of indicators in the Box–Cox transformed space.

Therefore, in the transformed space, the power mean suffers from the same drawbacks as the arithmetic mean, that is, the compensability and the substitutability. These issues should be considered in the aggregation phase to differentiate units with same power mean value and, as a consequence, to make rankings robust to the aggregation procedure. All these methods share the idea that the importance of an indicator should be related to the level of information it brings along.

The idea of penalizing units in different ways is shared by Mauro, Biggeri, and Maggino (2018) and Biggeri, Clark, Ferrannini, and Mauro (2019) who developed and applied the Multidimensional Synthesis of Indicators (MSI) approach to well-being, aggregating the indicators relative to different units with power means of different order. The order of the power mean is assumed to be a function of the arithmetic mean of the indicators, such that units with a lower indicator of arithmetic mean are associated with a lower order.

Surely, the choice of meaningful aggregative process relies on an appropriate choice of the aggregation and weighting schemes. Moreover, despite the fact that often they are implemented together, the aggregation and the weighting issues attain different and, in some ways, complementary aspects. In fact, the aggregation is related to the choice of a metric that quantifies the relationship or similarity between

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indicators. For example, the choice of the order p in the power mean approach is a metric choice. In fact, the power means of negative order penalize downwards the unbalance among indicators, emphasizing the improvements of the indicators with low values while penalizing those with high values. This is due to the fact that the metrics for negative orders reduce the distances between indicators with high values and increase the distances between indicators with low values. On the other hand, the choice of weights reflects the relative importance/relevance of the indicators to the overall objective of the analysis. This can be done a priori or a posteriori using data-driven methods. In the latter, the contribute of weighting to the construction of composite indicators is constrained to and limited by the choice of the aggregation method.

In the scientific literature, there are many papers addressing weighting methods. Just to mention a few, the papers Karagiannis and Karagiannis (2020), Karagiannis and Karagiannis (2023), Greco, Ishizaka, Tasiou, and Torrisi (2019), Curry and Faulds (1986), Kopalle and Hoffman (1992).

In Karagiannis and Karagiannis (2020), Karagiannis and Karagiannis (2023) several weighting methods based on information theory and completely data-driven are proposed. Specifically, in Karagiannis and Karagiannis (2020) the weighted arithmetic mean approach is used to aggregate the indicators and the Shannon entropy is used to derive a set of common weights. The idea is to assign more importance to the indicators that provide more information and, as a consequence, lower value of uncertainty, measured through the Shannon entropy. In Karagiannis and Karagiannis (2023) the authors determine the weights endogenously using four distance-based methods: the maximizing deviations, the weighted least square deviation from the mean, the weighted least square deviation from the ideal, and the weighted least square dissimilarity.

The evaluation of the uncertainty in the weights for composite indicators is a key ingredient of Greco et al. (2019). The problem is addressed by means of the Stochastic Multiattribute Acceptability Analysis. This analysis allows for the computation of the probability that a unit attains a given ranking position and the probability that a unit is better than another. In particular, following the weighted arithmetic mean aggregation approach, the authors compute, for each unit, the probability distribution of weights, its mean (μ) and standard deviation (σ). Moreover, they construct the “efficient frontier” in the plane $\sigma - \mu$. The efficient frontier is made by the units that provide the best trade-off between standard deviation and mean.

In Curry and Faulds (1986), Kopalle and Hoffman (1992) the authors investigate the sensitivity to weights of the composite indicators by theoretical and computational points of view. This is done comparing the correlations among ranking associated with composite indicators obtained as arithmetic means with different set of weights. From the analysis it emerges that positively correlated indicators are less sensitive to the choice of weights with respect to negatively correlated indicators. For an extensive and detailed guide to the construction and use of composite indicators we refer to OECD (2008).

In this paper, the focus is the aggregation scheme and a generalization to include weights. Specifically, in line with the works of Mauro et al. (2018), Biggeri et al. (2019), Rogge (2018a) and Rogge (2018b), we propose a new aggregation approach that penalizes the power mean associated with units characterized by larger heterogeneity. The penalization consists in a factor which multiplies the mean and accounts for the horizontal heterogeneity among indicators. We build this factor for each unit, first by computing the power mean of the indicators associated with the unit. Second, we scale the indicators by their power mean. Third, we apply the Box–Cox transformation to the scaled indicators. Finally, we compute the variance of the transformed indicators and the counter image of this variance using the Box–Cox function. The counter image is the resulting penalization factor. This factor is a kind of “variance” in the transformed space and, therefore, can be interpreted as the relative error or loss of information associated with the i th unit as the power mean is substituted for the vector of

the transformed indicators. Interestingly, the penalized power mean of order one coincides with the Mazziotta Pareto Index (Mazziotta & Pareto, 2016).

Moreover, we implement a Benefit of the Doubt (BoD)-based weighted version of the penalized power means for constructing an Human Development Index (HDI) (for more details, see Rogge (2018a) and Rogge (2018b)). The BoD-based weights are considered with the aim of showing that the proposed aggregation is less sensitive to the choice of weights with respect to alternative approaches. This conclusion is motivated by the conjecture that the penalization acts as a unit-dependent system of weights, neutralizing partially the importance attributed by the weights to each indicator, and, as a consequence, originating a more robust composite indicator. It should be noted that the BoD weights are derived solving an optimization problem, and, for this reason, they are not always unique. The non-uniqueness of BoD weights is a crucial task extensively investigated by several authors (see, among others, Cooper, Ruiz, and Sirvent (2007)). Despite their efforts, to the best of our knowledge, there are not standard selection procedures among the multiple optima. Here, the use of BoD approach is only illustrative to study the effects of weights on the penalized power means in comparison with their non-penalized versions. Therefore, although the analysis of the robustness of our approach to different set of weights, associated with multiple optima, deserves attention and further investigation, it falls beyond the scope of paper.

The penalization approach proposed in this paper is fully data-driven and can be effectively applied in many other fields, such as environmental indices (Sadiq, Haji, Cool, & Rodriguez, 2010), fuzzy rule-based systems, pattern recognition, decision-making problems (Khameneh & Kilicman, 2020), and weighted voting systems (Bustince, Jurio, Pradera, Mesiar, & Beliakov, 2013). We also investigate whether it is possible to select the order of the mean to obtain an aggregative approach that provides composite indicators whose induced unit rankings are less “sensitive” to the order p used in the aggregation. The latter is a very delicate issue because recent investments in innovation and green policies have imposed the introduction of “reliable and robust” ranking to make decisions.

Furthermore, the penalization approach also extends to weighted power means, which are therefore applicable to the BoD approach as illustrated in Sections 3 and 4.

There are three main findings: the penalized power means satisfy the properties characterizing weakly monotone aggregation functions; the penalization reduces ranking variations while differentiating units with same means; and the zero-th order (i.e., geometric mean) provides composite indicators whose rankings are the closest to rankings obtained by different power mean approaches, in that the zero-th order mean minimizes the variation of the rankings with a set of order p . Interestingly, the penalized power means are power means applied to penalized indicators.

The paper is organized as follows. Section 2 introduces the penalized power means and some properties of this family are proven. Section 3 extends the penalization to weighted power means and Section 4 proposes an empirical analysis of the HDI in 2019, comparing the country rankings of the penalized/non-penalized power mean aggregation to penalized/non-penalized BoD aggregation. Section 5 draws some conclusions. Appendix A provides some auxiliary results necessary to prove that the penalized power means are weakly monotone aggregation functions. Appendix B contains the proofs of the main propositions of Section 2. Appendix C contains the detailed tables of ranking relative to the numerical experiments of Section 4. Finally, Appendix D analyzes the effect of penalization on BoD approach when relative importance constraints on the weights are imposed.

2. A new class of composite indicators

Let $I_{i,j}$ be the value of the indicator j , $j = 1, 2, \dots, m$, relative to unit i , $i = 1, 2, \dots, n$, such that $I_{i,j}$ belongs to the interval $[a, b]$, where $b > a > 0$. Let the superscript T denote the transpose operator and $\underline{I}_i = [I_{i,1} \ I_{i,2} \ \dots \ I_{i,m}]^T$ the (column) vector of indicators relative to the i -th unit, $i = 1, 2, \dots, n$. For $i = 1, 2, \dots, n$, the power mean of order p associated to \underline{I}_i is defined by

$$M_{p,i} = \begin{cases} \left(\frac{1}{m} \sum_{j=1}^m I_{i,j}^p \right)^{\frac{1}{p}}, & p \neq 0, \\ \left(\prod_{j=1}^m I_{i,j} \right)^{\frac{1}{m}}, & p = 0. \end{cases} \quad (1)$$

The arithmetic mean, geometric mean, and harmonic mean are special cases of the power mean for $p = 1$, $p = 0$, and $p = -1$, respectively.

For $i = 1, 2, \dots, n$ the composite indicator $M_{p,i}$ can be read as solution to the following optimization problem (Berger & Casella, 1992):

$$\min_{c>0} F_p(c; \underline{I}_i), \quad (2)$$

where:

$$F_p(c; \underline{I}_i) = \frac{1}{m} \sum_{j=1}^m (h_p(I_{i,j}) - h_p(c))^2 \quad (3)$$

is the (information) loss function (or, the penalty function, to use the nomenclature of Calvo and Beliakov (2010)), and $h_p(x)$ is the Box–Cox transformation (Box & Cox, 1964):

$$h_p(x) = \begin{cases} \frac{x^p - 1}{p}, & p \neq 0, \\ \ln x, & p = 0. \end{cases} \quad (4)$$

Note that, for any p , the function $h_p(x)$, $x > 0$, is strictly increasing and satisfies the condition $h_p(1) = 0$.

The claim mentioned above follows from two simple observations.

First, for $i = 1, 2, \dots, n$, the solution to problem (2) is the constant c , such that $h_p(c)$ is the arithmetic mean of values $h_p(I_{i,1})$, $h_p(I_{i,2})$, \dots , $h_p(I_{i,m})$. The values $h_p(I_{i,j})$, $j = 1, 2, \dots, m$, are interpreted as the values of the statistical (latent) variable Y_i which describes the unit i in the “transformed space”. For later convenience, these values are collected in the vector $h_p(\underline{I}_i) = [h_p(I_{i,1}) \ h_p(I_{i,2}) \ \dots \ h_p(I_{i,m})]^T$.

Second, the arithmetic mean of the values $h_p(I_{i,j})$, satisfies

$$M_1(h_p(\underline{I}_i)) = \frac{1}{m} \sum_{j=1}^m h_p(I_{i,j}) = h_p(M_{p,i}), \quad i = 1, 2, \dots, n. \quad (5)$$

Eq. (5) allows us to conclude that the optimal value of c , the solution to problem (2), is $c = M_{p,i}$.

Therefore, in the p -transformed space – the space obtained by transforming the m dimensional vectors via the Box–Cox function of order p – the p -order generalized mean acts as the arithmetic mean.

Moreover, for any unit i , $i = 1, 2, \dots, n$, we can measure the error (loss of information) caused by substituting the transformed values of the indicators, $h_p(I_{i,j})$, $j = 1, 2, \dots, m$, with $h_p(M_{p,i})$, evaluating the objective function F_p at its optimizer:

$$F_p(M_{p,i}; \underline{I}_i) = \frac{1}{m} \sum_{j=1}^m (h_p(I_{i,j}) - h_p(M_{p,i}))^2, \quad i = 1, 2, \dots, n. \quad (6)$$

It is easy to see that for any unit i , $i = 1, 2, \dots, n$, this error coincides with the (biased) sample variance of a statistical variable, Y_i , whose values are given in the vector $h_p(\underline{I}_i)$. Here and in the rest of paper, we denote this variance with $S_{p,i}^2$.

Therefore, for $i = 1, 2, \dots, n$, the quantity $h_p^{-1}(S_{p,i}^2)$ is a measure of the information loss caused by replacing \underline{I}_i with $M_{p,i}$. Note that the

size of $h_p^{-1}(S_{p,i}^2)$ strongly depends on $M_{p,i}$; hence, variances of the unit i computed with different p -orders are not comparable.

We overcome this drawback by scaling the indicators referring to the same unit by a specific criterion that removes the dependence from the power mean. To this end, we consider the vector of scaled indicators, $\tilde{\underline{I}}_i = [\tilde{I}_{i,1} \ \tilde{I}_{i,2} \ \dots \ \tilde{I}_{i,m}]^T$, where

$$\tilde{I}_{i,j} = \frac{I_{i,j}}{M_{p,i}}, \quad j = 1, 2, \dots, m, \quad i = 1, 2, \dots, n. \quad (7)$$

Bearing in mind that $h_p(1) = 0$, it follows from the homogeneity property of the p -order power means that $M_p(\tilde{\underline{I}}_i) = 1$ and $h_p(M_p(\tilde{\underline{I}}_i)) = h_p(1) = 0$ for $i = 1, 2, \dots, n$. As a consequence, the error (loss of information) caused by substituting the vector of indicators $h_p(\tilde{\underline{I}}_i)$ with $h_p(M_p(\tilde{\underline{I}}_i)) = h_p(1) = 0$ is given by

$$L_{p,i} = \frac{1}{m} \sum_{j=1}^m (h_p(\tilde{I}_{i,j}) - h_p(1))^2 = \frac{1}{m} \sum_{j=1}^m [h_p(\tilde{I}_{i,j})]^2, \quad i = 1, 2, \dots, n. \quad (8)$$

Note that, independent of the fact that the optimizer of problem (2) for the vector \underline{I}_i is the p -order power mean $M_{p,i}$, scaling the indicator by the optimizer (as done in (7)) makes the optimizer of problem (2) for the resulting scaled vector $\tilde{\underline{I}}_i$ equal to 1, $i = 1, 2, \dots, n$. This means that the corresponding loss of information is equal to the L^2 norm of vector $h_p(\tilde{\underline{I}}_i)$ (as in (8)).

However, the choice of considering scaled indicators does not guarantee that the loss of information ranges in a given interval. To overcome this difficulty, we define:

$$\tilde{S}_{p,i}^2 := KL_{p,i}, \quad i = 1, 2, \dots, n, \quad (9)$$

where $K > 0$ is a real constant. Commonly, the choice K equal to 1 is strongly recommended except for some circumstances explained in Definition 1.

For $i = 1, 2, \dots, n$, the quantity

$$h_p^{-1}(\tilde{S}_{p,i}^2) = \begin{cases} \left(1 + p \tilde{S}_{p,i}^2 \right)^{\frac{1}{p}}, & p \neq 0, \\ \exp(\tilde{S}_{0,i}^2), & p = 0, \end{cases} \quad (10)$$

is independent of the size of $\tilde{M}_{p,i}$. It measures the relative information loss caused by replacing \underline{I}_i with $M_{p,i}$. The higher the value of $h_p^{-1}(\tilde{S}_{p,i}^2)$, the greater the loss of information caused by considering $M_{p,i}$ instead of the sub-indicator vector \underline{I}_i .

We use $h_p^{-1}(\pm \tilde{S}_{p,i}^2)$ to penalize the power mean of order p . Specifically, for $i = 1, 2, \dots, n$, the penalized power mean of order p associated with the indicator vector \underline{I}_i is defined by

$$PM_{p,i}^{\pm} = M_{p,i} g_{p,i}^{\pm}, \quad (11)$$

where $g_{p,i}^{\pm}$ is the penalization factor:

$$g_{p,i}^{\pm} = h_p^{-1}(\pm \tilde{S}_{p,i}^2) = (1 \pm p \tilde{S}_{p,i}^2)^{\frac{1}{p}} = \begin{cases} \left(1 \pm p \tilde{S}_{p,i}^2 \right)^{\frac{1}{p}}, & p \neq 0, \\ \exp(\pm \tilde{S}_{0,i}^2), & p = 0. \end{cases} \quad (12)$$

The sign in (11), (12) depends on the phenomenon considered. Specifically, if increasing variations of the indicator correspond to positive variations of the phenomenon (positive polarity), we choose the sign $-$, otherwise (negative polarity) we choose the sign $+$.

Furthermore, the scaling in (7) ensures that the term $h_p^{-1}(\pm \tilde{S}_{p,i}^2)$ penalizes the score of each unit (the p -order power mean of the indicators) independent of the value of the power mean itself with a quantity that is directly proportional to the “horizontal variability” of the indicators. The aim of the penalization is to favor the units that, given identical power means, are more balanced among the indicators. This is the idea underlying the “Method of Penalties by Coefficient of

Variation”, introduced by [Mazziotta and Pareto \(2016\)](#), which adjusts the arithmetic mean by a penalization coefficient that, for each unit, is a function of the coefficient of variation defining the Mazziotta Pareto Index (MPI). Indeed, the indicator in (11) when $p = 1$ is the Mazziotta Pareto Index, thereby setting in the new class of penalized power means on firm foundations.

We now take a deeper look at the behavior of the penalization term $g_{p,i}^-$ (i.e., positive polarity) as a function of the order p , for $i = 1, 2, \dots, n$. Bearing in mind that $\tilde{S}_{p,i}^2$ is nonnegative, the penalization factor $(1 - p\tilde{S}_{p,i}^2)^{\frac{1}{p}}$ is positive only if the inequality $p\tilde{S}_{p,i}^2 \leq 1$ holds. The latter may or may not hold depending on the sign of p . In fact, we only prove that $\tilde{S}_{p,i}^2$ is a positive non-increasing function of p . Thus, for $p > 0$ the monotonicity $\tilde{S}_{p,i}^2$ just mentioned, along with the properties $\lim_{p \rightarrow +\infty} p\tilde{S}_{p,i}^2 = 0$ and $\lim_{p \rightarrow 0^+} p\tilde{S}_{p,i}^2 = 0$, imply that the inequality $p\tilde{S}_{p,i}^2 \leq 1$ holds for sufficiently large and small values of p .

In contrast to the case $p > 0$, when p is zero or negative, the penalization term is always nonnegative. Furthermore, when $p < 0$ the penalization term, $(1 - p\tilde{S}_{p,i}^2)^{\frac{1}{p}}$, is smaller than one since the exponent $1/p$ is negative and the base of the power, $1 - p\tilde{S}_{p,i}^2$, is greater than one. This implies that no constraints are necessary on the magnitude of $p\tilde{S}_{p,i}^2$ when $p < 0$. In the case $p = 0$, the penalization is less than one for positive polarity $\exp(-\tilde{S}_{0,i}^2)$.

For negative polarity of the sub-indicators, the penalization, $(1 + p\tilde{S}_{p,i}^2)^{\frac{1}{p}}$, $p \neq 0$ and $\exp(\tilde{S}_{0,i}^2)$, $p = 0$, is larger than one, since higher values of the composite indicator indicate lower ranking positions due to the negative polarity.

We now provide a formal definition of the penalized power mean of order p as a weakly monotone aggregation function (see [Proposition 4](#)) and we prove some properties. To simplify the notation, in the rest of this section, where it is not necessary, we drop the subscript i .

Definition 1 (Penalized Power Mean). Given a non-empty interval $[a, b] \subseteq (0, +\infty)$ and the vector of indicators $\underline{I} = [I_1, I_2, \dots, I_m]^T \in [a, b]^m$, the penalized power means of order p of \underline{I} are the functions

$$PM_p^\pm : [a, b]^m \rightarrow [a, b]$$

defined by

$$PM_p^\pm(\underline{I}) = M_p(\underline{I})g_p^\pm(\underline{I}), \tag{13}$$

where

$$M_p(\underline{I}) = \begin{cases} \left(\frac{1}{m} \sum_{j=1}^m I_j^p \right)^{\frac{1}{p}}, & p \neq 0, \\ \left(\prod_{j=1}^m I_j \right)^{\frac{1}{m}}, & p = 0, \end{cases} \tag{14}$$

is the power mean of order p of \underline{I} ,

$$g_p^\pm(\underline{I}) = (1 \pm p\tilde{S}_p^2(\underline{I}))^{\frac{1}{p}} \tag{15}$$

is the penalization factor associated with \underline{I} ,

$$\tilde{S}_p^2(\underline{I}) = \frac{K}{m} \sum_{j=1}^m \left[h_p \left(\frac{I_j}{M_p(\underline{I})} \right) \right]^2, \tag{16}$$

where $K = 1$ unless a different choice of K is necessary to preserve the range invariance.

We now establish the following elementary features of the penalized means when different units are compared.

Proposition 1. The penalized power mean defined in (11) satisfies the following properties:

$$1. (PM_{p,i}^+)^p = (PM_{p,i}^-)^p + 2p(M_{p,i})^p \tilde{S}_{p,i}^2 \text{ for } p \neq 0.$$

$$2. PM_{0,i}^+ = PM_{0,i}^- \exp \left\{ 2 \tilde{S}_{0,i}^2 \right\}.$$

3. Given two units k and h ($k \neq h$) with $M_{p,k} = M_{p,h}$, we have

$$PM_{p,k}^- > PM_{p,h}^- \text{ iff } \tilde{S}_{p,k}^2 > \tilde{S}_{p,h}^2, \\ PM_{p,k}^+ > PM_{p,h}^+ \text{ iff } \tilde{S}_{p,k}^2 > \tilde{S}_{p,h}^2.$$

4. Given two units k and h ($k \neq h$) with $M_{p,k} > M_{p,h}$, for $p \neq 0$, we have

$$PM_{p,k}^- > PM_{p,h}^- \text{ iff } M_{p,k}^p - M_{p,h}^p > p \left(M_{p,k}^p \tilde{S}_{p,k}^2 - M_{p,h}^p \tilde{S}_{p,h}^2 \right), \\ PM_{p,k}^+ > PM_{p,h}^+ \text{ iff } M_{p,k}^p - M_{p,h}^p > p \left(M_{p,h}^p \tilde{S}_{p,h}^2 - M_{p,k}^p \tilde{S}_{p,k}^2 \right).$$

5. Given two units k and h ($k \neq h$) with $M_{0,k} > M_{0,h}$, we have

$$PM_{0,k}^- > PM_{0,h}^- \text{ iff } \frac{M_{0,k}}{M_{0,h}} > \exp \left\{ \tilde{S}_{0,k}^2 - \tilde{S}_{0,h}^2 \right\}, \\ PM_{0,k}^+ > PM_{0,h}^+ \text{ iff } \frac{M_{0,k}}{M_{0,h}} > \exp \left\{ \tilde{S}_{0,h}^2 - \tilde{S}_{0,k}^2 \right\}.$$

Proof. The proof follows easily from definition (11).

The following results investigate the properties of the penalized mean of order p to investigate whether the term “mean” is used appropriately.

The main result is [Proposition 4](#), where we show that the penalized power means satisfy the properties necessary to be an appropriate aggregative tool for composite indicators.

Before presenting the main proposition, we observe that the loss of information associated with the vector \underline{I} , $\tilde{S}_p^2(\underline{I})$, appearing in formula (16) does not increase when all the indicators are translated by the same constant.

Proposition 2. Let $\underline{c} = [c, c, \dots, c]^T \in \mathbb{R}^m$ be the vector with entries equal to a constant $c > 0$. The derivative of $\tilde{S}_p^2(\underline{I} + \underline{c})$ with respect to c is nonpositive, that is, $\tilde{S}_p^2(\underline{I} + \underline{c})$ is a non-increasing function of c .

Proof. See [Appendix B](#).

Note that [Proposition 2](#) says that by translating the indicators, we reduce the effect of the penalization. Thus, transformations of the original indicators involving translation affects the penalized means.

We now illustrate the properties of the penalized power mean.

Proposition 3. The penalized power means of order p , $PM_p^\pm(\underline{I})$ defined in (13) satisfy the following properties:

1. $PM_p^\pm(\underline{c}) = c$, where $c > 0$,
2. $\lim_{c \rightarrow 0} PM_p^\pm(\underline{c}) = 0$, where $\underline{c} = [c, c, \dots, c]^T$, such that $c > 0$,
3. $PM_p^+(\underline{I}) \geq M_p(\underline{I}) \geq PM_p^-(\underline{I})$,
4. $PM_p^+(\underline{I}) = PM_p^-(\underline{I}) = M_p(\underline{I})$ iff $\tilde{S}_p^2(\underline{I}) = 0$,
5. $\lim_{p \rightarrow -\infty} PM_p^\pm(\underline{I}) = \min_{j=1,2,\dots,m} I_j$,
6. $\lim_{p \rightarrow +\infty} PM_p^\pm(\underline{I}) = \max_{j=1,2,\dots,m} I_j$,
7. $\lim_{p \rightarrow 0} PM_p^\pm(\underline{I}) = \exp \left\{ \pm \tilde{S}_0^2(\underline{I}) \right\}$,
8. $PM_p^-(\underline{I}) \leq \max(\underline{I})$,
9. $\min(\underline{I}) \leq PM_p^+$,
10. $PM_p^\pm(c \underline{I}) = c PM_p^\pm(\underline{I})$ for any $c > 0$ such that $c \underline{I} \in [a, b]^m$,
11. $PM_p^-(\underline{I} + \underline{c}) \geq PM_p^-(\underline{I})$ for any $\underline{c} = [c, c, \dots, c]^T$ such that $c \geq 0$ and $\underline{I} + \underline{c} \in [a, b]^m$,
12. $PM_p^+(\underline{I} + \underline{c}) \leq PM_p^+(\underline{I})$ for any $\underline{c} = [c, c, \dots, c]^T$ such that $c \geq 0$ and $\underline{I} + \underline{c} \in [a, b]^m$,
13. $a \leq PM_p^\pm(\underline{I}) \leq b$.

Proof. See [Appendix B](#).

Note that Property 13 guarantees that the penalized power mean are range preserving. Moreover, Properties 5 and 6 in Proposition 3 imply that the penalization has no effect when the power mean of order $-\infty$ (i.e., the minimum function) or $+\infty$ (i.e., the maximum function) is considered. In fact, in the case of positive polarity and negative polarity, the minimum and maximum functions, respectively, already lead to the maximum penalization for unbalanced values of the indicators, so they need no further penalizations. Properties 11 and 12 state that the penalized power means exhibit weakly monotonic behavior (for more details about weakly monotonicity and the definition of aggregation function we refer, respectively, to Wilkin, Beliakov, and Calvo (2014), Grabisch, Marichal, Mesiar, and Pap (2011)).

Proposition 4. *The penalized power means (13) are weakly monotone aggregation functions.*

Proof. The proof follows easily from Properties 1, 2, 11, 12 and 13 of Proposition 3.

Note that the penalized power means (13) associated with the vector of indicators \underline{I} are power means applied, respectively, to the vector of penalized indicators $\underline{J}^\pm = [J_1^\pm J_2^\pm \dots J_m^\pm]^T$, where:

$$J_j^\pm = I_j g_p^\pm, \quad j = 1, 2, \dots, m.$$

Finally, as mentioned in the Introduction, we prove that the penalized mean of order one is the Mazziotta Pareto Index already used by the Italian central statistical bureau.

Proposition 5. *The penalized power mean of order one, $PM_1^\pm(\underline{I})$, coincides with the MPI.*

Proof. Substituting (4) for $p = 1$ in (16) and bearing in mind that $K = 1$, we have

$$\begin{aligned} \tilde{S}_1^2(\underline{I}) &= \frac{1}{m} \sum_{j=1}^m (\tilde{I}_j - 1)^2 = \frac{1}{m} \sum_{j=1}^m \left(\frac{I_j}{M_1(\underline{I})} - 1 \right)^2 = \frac{\frac{1}{m} \sum_{j=1}^m (I_j - M_1(\underline{I}))^2}{M_1^2(\underline{I})} \\ &= \frac{S_1^2(\underline{I})}{M_1(\underline{I})^2}, \end{aligned} \tag{17}$$

where

$$S_1^2(\underline{I}) = \frac{1}{m} \sum_{j=1}^m (I_j - M_1(\underline{I}))^2 \tag{18}$$

is the (biased) sample variance of vector \underline{I} .

Substituting (17) into (15) for $p = 1$, we have

$$PM_1^\pm(\underline{I}) = M_1(\underline{I}) \left(1 \pm \frac{S_1^2(\underline{I})}{M_1(\underline{I})^2} \right), \quad i = 1, 2, \dots, n, \tag{19}$$

that is, the MPI.

3. From penalized power means to penalized weighted power means

In this section, we introduce the penalization for the weighted power mean aggregation approach. This extension allows us to apply the penalization to the composite indicators obtained via the “direct” Benefit of the Doubt (BoD) approach illustrated in Cherchye, Moesen, Rogge, and Van Puyenbroeck (2007), Rogge (2018a) and Rogge (2018b). The weights of the BoD composite indicators are country-specific, so these indicators are flexible in capturing differences among the countries. As mentioned in the Introduction, the main focus of the paper is the presentation of the penalized power mean approach and its weighted version. The inclusion of weights is done for studying the sensitivity of the penalized power means to the choice of weights in comparison with their non-penalized versions. To this end, we use the Benefit of the Doubt (BoD) approach to illustrate this study.

For $i = 1, 2, \dots, n$, the weighted power mean of order $p \in \mathbb{R}$ is defined as follows:

$$M_{p,i}^w = M_p^w(\underline{I}_i) = \begin{cases} \left(\sum_{j=1}^m w_{i,p,j} I_{i,j}^p \right)^{\frac{1}{p}}, & p \neq 0, \\ \prod_{j=1}^m I_{i,j}^{w_{i,0,j}}, & p = 0, \end{cases} \tag{20}$$

where the weights $w_{i,p,j}$ are non-negative and depend on the unit i (country), the order of power mean p , and the sub-indicator j .

Assuming that the weights sum to one, i.e., $\sum_{j=1}^m w_{i,p,j} = 1$, we introduce the “penalized” weighted power mean of order p , viewing the pairs $(h(I_{i,1}), w_{i,p,1}), (h(I_{i,2}), w_{i,p,2}), \dots, (h(I_{i,m}), w_{i,p,m})$ as the frequency distribution of a statistical variable, Y_i , which describes the “ i th unit”.

It is easy to prove that

$$h_p(M_{p,i}^w) = M_1^w(h_p(\underline{I}_i)) = \sum_{j=1}^m w_{i,p,j} h_p(I_{i,j}), \quad i = 1, 2, \dots, n, \tag{21}$$

that is, as in Section 2, in the p -transformed space, the p -order weighted generalized mean acts as the weighted arithmetic mean.

Hence, arguing as in Section 2, for any unit i , we measure the loss of information that originates from replacing the vector of indicators $h_p(\underline{I}_i)$ with $h_p(M_{p,i}^w)$, evaluating the objective function F_p^w at its optimizer:

$$S_{w,p,i}^2 := F_p^w(M_{p,i}^w; \underline{I}_i) = \sum_{j=1}^m w_{i,p,j} (h_p(I_{i,j}) - h_p(M_{p,i}^w))^2, \quad i = 1, 2, \dots, n. \tag{22}$$

We can interpret this loss of information in unit i as the variance of the statistical variable Y_i .

Finally, we introduce the vector of the scaled indicators as in Eq. (7), i.e., $\tilde{\underline{I}}_i^w = [\tilde{I}_{i,1}^w, \tilde{I}_{i,2}^w, \dots, \tilde{I}_{i,m}^w]^T$, with $\tilde{I}_{i,j}^w = I_{i,j} / M_{p,i}^w$. Proceeding as in Section 2, for $i = 1, 2, \dots, n$, we define the weighted penalized power mean of order p as follows:

$$PM_{w,p,i}^\pm = M_{w,p,i}^w g_{w,p,i}^\pm, \tag{23}$$

where $g_{w,p,i}^\pm$ is the penalization factor:

$$g_{w,p,i}^\pm = h_p^{-1}(\pm \tilde{S}_{w,p,i}^2) = (1 \pm p \tilde{S}_{w,p,i}^2)^{\frac{1}{p}} = \begin{cases} (1 \pm p \tilde{S}_{w,p,i}^2)^{\frac{1}{p}}, & p \neq 0, \\ \exp(\pm \tilde{S}_{w,0,i}^2), & p = 0, \end{cases} \tag{24}$$

in which

$$\tilde{S}_{w,p,i}^2 = K \tilde{L}_{w,p,i}, \tag{25}$$

and

$$\tilde{L}_{w,p,i} = \sum_{j=1}^m w_{i,p,j} (h_p(\tilde{I}_{i,j}^w) - h_p(1))^2 = \sum_{j=1}^m w_{i,p,j} (h_p(\tilde{I}_{i,j}^w))^2. \tag{26}$$

In conclusion, formula (23) is the penalized version of the weighted power means.

We note that the definition of penalized weighted power means of order p , see Eq. (23), continues to hold when the weights do not sum to one. In this case, we interpret the quantity $\tilde{S}_{w,p,i}^2$ as the loss of information generated by substituting the power p of the sub-indicator $I_{i,j}^p$ with the power p of its mean, $(M_{i,p}^w)^p$, weighted by the importance of the sub-indicators. The loss is zero if and only if the ratio $I_{i,j}^p / (M_{i,p}^w)^p$ equals one that is, $I_{i,j}$ equals $M_{w,p,i}^w$.

In the following section, we apply this generalization to the “direct” BoD composite indicators as proposed in Rogge (2018b).

Table 1

Descriptive statistics of the sub-indicators of the HDI (left panel); correlation coefficients of the sub-indicators (right panel).

Sub-indicator:	<i>H</i>	<i>E</i>	<i>I</i>
Min.	0.5123	0.2506	0.3052
1st Qu.	0.7292	0.5289	0.5882
Median	0.8308	0.6833	0.7318
Mean	0.8110	0.6592	0.7145
3rd Qu.	0.8908	0.7939	0.8590
Max	0.9985	0.9456	1.00
st.dev	0.1136	0.1724	0.1736

	<i>H</i>	<i>E</i>	<i>I</i>
<i>H</i>	1	0.8176	0.8412
<i>E</i>	0.8176	1	0.8653
<i>I</i>	0.8412	0.8653	1

4. Empirical analysis

In this section, we investigate whether the ranking induced by power means of order p and the corresponding penalized power means are different and, more interestingly, whether it is possible to choose the order p to minimize the differences in ranking obtained for different order pairs (p, p') .

This analysis aims to develop composite indicators that are robust to the order of the power mean used to aggregate the composite indicator itself. In the empirical analysis illustrated in this section K (see Eqs. (9) and (25)) always equals 1 since in our application the penalized power mean and the penalized weighted power mean are always range preserving.

As stressed in Guh, Po, and Lee (2008) and Rogge (2018b), the choice of the order p depends on the objective/attitude of the decision maker, so it is a sort of “behavioral parameter”. The parameter p can be chosen a priori based on the expert judgement, or a posteriori based on the indicator values. For example, the a priori choice can be done in a way such that the resulting score favors the improvements of the worst-performing indicators. In this case, as explained in the Introduction, a power mean of negative order should be used. Otherwise, if we are interested in a composite indicator that favors the improvements of the best-performing indicators, power means of positive order do for us. On the other hand, the order of the mean can be chosen a posteriori based on the distribution of the indicator values. For example, if the data is expected to have outliers or extreme values, a higher value of p might be more appropriate to reduce the impact of outliers. Conversely, if the data is highly skewed towards lower values, a lower value of p might be preferred to give more weight to smaller values. Alternatively, if we interpret the Box–Cox transformation as a utility function with Constant Relative Risk Aversion (CRRA), the parameter p can be expressed as $1 - \gamma$, where γ represents the relative risk aversion coefficient of the decision maker. The loss function measures the loss that a decision maker with CRRA utility associates to substituting the vector of indicators with the composite indicator.

We look for a p^* order which induces a unit ranking as close as possible to the ranking induced by any alternative p order. This p^* order may be considered “fair” since it induces a ranking which is not too sensitive to the power mean order.

We carried out this analysis on the classical and penalized power means as well as on the corresponding weighted means. The weights of the latter are constructed as suggested in Rogge (2018b).

In detail, we use

$$r^m(p; \underline{I}) = (r_1^m(p; \underline{I}), r_2^m(p; \underline{I}), \dots, r_n^m(p; \underline{I}))$$

$$\text{and } r^{pm}(p; \underline{I}) = (r_1^{pm}(p; \underline{I}), r_2^{pm}(p; \underline{I}), \dots, r_n^{pm}(p; \underline{I}))$$

to denote the ranking of units implied by the composite indicator obtained with the classical and penalized p -order means, respectively.

We define the “fair” p -value the solution to the following problem:

$$\min_{p \in \mathcal{P}} F(p) := \sum_{p' \in \mathcal{P}} \sum_{j=1}^n |r_j^m(p; \underline{I}) - r_j^m(p'; \underline{I})|, \tag{27}$$

and a similar problem can be formulated for the penalized mean.

We conduct our study on the freely downloadable data of sub-indicators that define the Human Development Index (HDI) relative to

$n = 189$ countries in the year 2019. The data of sub-indicators were downloaded from the UNDP Data Center (<https://hdr.undp.org/data-center>).

Specifically, the HDI is obtained from three sub-indicators – life expectancy, education, and income – aggregated by the geometric mean function with equal weights (i.e., Eq. (1) with $p = 0$):

$$HDI = (H * E * I)^{1/3},$$

where the health dimension (H) is measured through the life expectancy indicator, the education dimension (E) is the arithmetic mean of the two education indices (mean years of schooling and expected years of schooling), and the gross national income per capita (I) is a proxy that accounts for the standard of living.

Table 1 shows the descriptive statistics of the sub-indicators. We observe that the sub-indicators are positively correlated.

4.1. Power mean aggregative approach: unit-independent weights

We compute the composite indicators on HDI data using as an aggregation tool both the power mean and the penalized power mean for different values of the p -order. Specifically, we choose $p_l = -M + (2l - 1)$, $l = 1, 2, \dots, M$, so the p -orders considered are integer values varying from $-M + 1$ to $M - 1$. That is, in (27) we set $\mathcal{P} = \{p_1, p_2, \dots, p_M\}$. We choose $M = 11$ since in the literature, the order usually varies from -5 to 5. Furthermore, we use $CM(p)$ to denote the classical power mean of order p and $PM(p)$ for the corresponding penalized version, while the ranking induced on country i , $i = 1, 2, \dots, n$, ($n = 189$) is denoted with $r_{CM}(i, p)$ and $r_{PM}(i, p)$, respectively.

We first analyze the distribution of the ranking difference $d_i(p) = r_{PM}(i, p) - r_{CM}(i, p)$, $i = 1, 2, \dots, n$, induced by the composite indicators defined by the penalized power mean and the power mean, respectively. Fig. 1 shows the distribution of $d_i(p)$, $i = 1, 2, \dots, n$, for negative values of p , $p = -5, -4, -3, -2, -1$, and $p = 0$ (left panel), and for positive p , $p = 1, 2, 3, 4, 5$, and $p = 0$ (right panel). The distributions shown in Fig. 1 are not symmetric. This finding is confirmed by the positive skewness of all distributions in Fig. 1, i.e., 1.189, 1.571, 1.598, 1.806, 1.537, 1.047, 0.564, 0.590, 0.285, 0.756, 0.765, respectively for p varying from -5 to 5. This implies that the penalized power mean more frequently provides a larger rank than the non-penalized power mean. Finally, the standard deviation of the distributions increases with p (i.e., 1.741, 1.839, 2.174, 2.523, 2.819, 2.932, 2.935, 2.995, 2.971, 3.238, 3.219) indicating that ranking differences are less volatile for negative orders.

Second, we solve problem (27) using the power mean and penalized power mean. Fig. 2 shows the graph of the objective function F of Problem (27) when the penalized (blue) and non-penalized (red) power means are used to aggregate the sub-indicators with different set of p ($p = -5, -4, \dots, 4, 5$ at the left panel and $p = -1, 0, \dots, 4, 5$ at the right panel). We see that the minimizer is the middle point of the interval, i.e., $p = 0$ (left panel) and $p = 2$ (right panel), for both aggregative approaches. More interestingly, the objective function F corresponding to penalized means is smaller than that of non-penalized means in both panels. This finding suggests that the ranking differences generated for different values of p reduce when penalized power means are used as an aggregative approach. The penalized geometric mean is the aggregative approach most suitable for reducing ranking variations

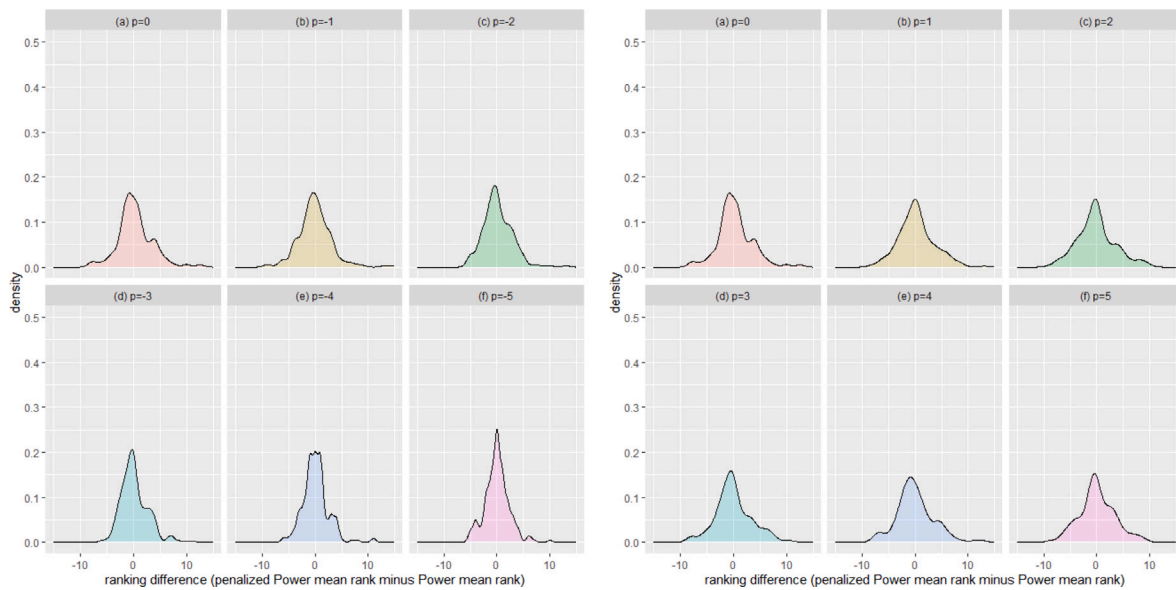


Fig. 1. Distribution of ranking difference $d_i(p) = r_{pM}(i, p) - r_{CM}(i, p)$, $i = 1, 2, \dots, n$, (i.e., penalized power mean of order p minus the corresponding power mean of order p) for $p = -5, -4, -3, -2, -1, 0$ (left panel) and for $p = 0, 1, 2, 3, 4, 5$ (right panel).

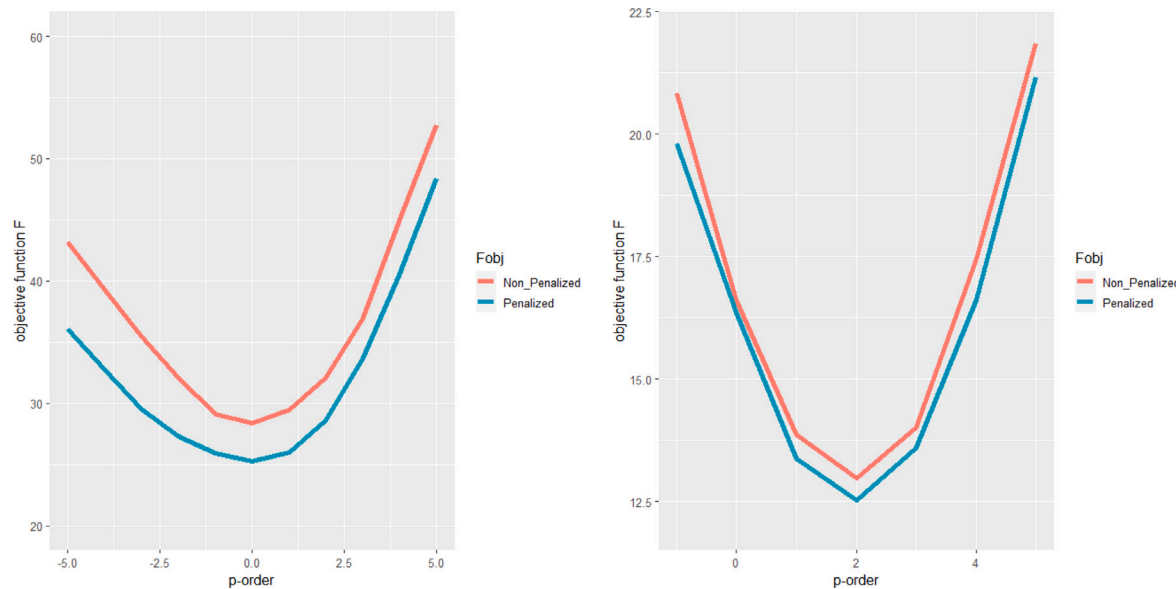


Fig. 2. Function F of Problem (27) when the power mean and penalized power mean are used to build the composite indicator and p varies from -5 to 5 (left panel) and from -1 to 5 (right panel).

when the interval of p of the minimization is symmetric with respect to the origin. This is expected, since the classical power means satisfy monotonicity with respect to the order p . Indeed, the monotonicity supports the fact that the middle point of the interval, where the minimization is carried out, is the solution to problem (27).

We note that the non-penalized geometric mean corresponds to the aggregative method used for the Human Development Index (HDI).

As Fig. 2 shows, the power means of order $p = -1$ (harmonic mean), $p = 0$ (geometric mean), and $p = 1$ (arithmetic mean) are those with the smallest ranking variations when compared with other (penalized/non-penalized) p -order power mean. We focus on these means to analyze countries in the first and last twenty positions of the HDI ranking.

Table 2 shows the countries ranked in the first (top panel) and last (bottom panel) twenty positions according to the HDI (i.e., geometric (rGM) mean), along with the rank of the harmonic (rHM) and arithmetic (rAM) means and the rank of their penalized versions

(i.e., columns rPHM, rPGM and rPAM). All the remaining results are available in Appendix C.

Table 2 shows that the penalization refines the ranking of the corresponding non-penalized approach. In fact, looking at the column of the penalized geometric mean in the top panel of Table 2, we see that Ireland is above Switzerland, Iceland is above Hong Kong, the United Kingdom is above Belgium, and Finland is above Singapore. These differences highlighted by the penalization are due to horizontal variability, which seems to be more pronounced in countries with a higher population density.

Looking at the panel at the bottom of Table 2, we notice that, according to the penalized geometric mean, Haiti is above Sudan, Guinea-Bissau is above Congo and Liberia, and, more interestingly, Sierra Leone is four positions above Burkina Faso. This finding does not confirm that the horizontal variability is linked to population density as noted in the first twenty countries.

Table 2

The first twenty (top panel) and last twenty (bottom panel) countries in the HDI ranking and the corresponding ranking obtained by the composite indicators aggregated with non-penalized/penalized power mean approaches for $p = -1$ (HM), 0 (GM), 1 (AM).

Country	Classical power mean aggregation			Penalized power mean aggregation		
	rHM	rGM	rAM	rPHM	rPGM	rPAM
Norway	1	1	1	1	1	1
Ireland	2	2	2	2	2	2
Switzerland	2	2	2	3	3	2
Hong Kong	5	4	4	6	6	5
Iceland	4	4	5	4	4	4
Germany	5	6	6	5	5	5
Sweden	7	7	7	7	7	7
Australia	9	8	8	8	8	9
Netherlands	7	8	8	8	8	7
Denmark	10	10	10	10	10	10
Finland	11	11	12	11	11	11
Singapore	12	11	10	15	12	12
Belgium	13	13	13	13	14	13
United Kingdom	13	13	13	12	12	13
New Zealand	15	15	15	14	15	15
Canada	16	16	16	15	16	16
United States	17	17	17	17	17	17
Austria	18	18	18	18	18	18
Israel	19	19	21	19	19	19
Liechtenstein	21	19	19	23	23	21
Haiti	167	170	171	167	167	168
Sudan	170	170	167	171	170	170
Gambia	172	172	173	169	169	172
Ethiopia	177	173	172	179	179	178
Malawi	175	174	174	177	177	175
Congo	174	175	177	173	174	174
Guinea-Bissau	173	175	180	170	170	173
Liberia	175	175	175	173	175	177
Guinea	177	178	179	176	175	175
Yemen	179	179	177	181	181	180
Eritrea	183	180	176	188	186	183
Mozambique	181	181	182	180	180	181
Burkina Faso	182	182	181	182	182	182
Sierra Leone	180	182	183	175	178	179
Mali	186	184	183	186	184	185
Burundi	185	185	185	184	184	186
South Sudan	184	186	186	183	183	184
Central African Republic	187	187	189	185	187	187
Chad	188	188	188	187	188	188
Niger	189	189	187	189	189	189

The main finding of this section is that the (non-penalized/penalized) geometric mean ($p = 0$) should be preferred to other power means, not only because it is non-compensative, but also because it solves Problem (27) as a middle point of the power order considered. The second finding is that the penalized mean refines the ranking of the corresponding non-penalized mean. This could be used to investigate the robustness of the HDI ranking.

4.2. Benefit of the Doubt aggregative approach: unit-dependent weights

We analyze the effect of penalization on the composite indicators defined by the Benefit of the Doubt (BoD) direct approach (see, Rogge (2018a) and Rogge (2018b)). This strand of the literature on composite indicators explores the methodological issue of weighting the sub-indicators, looking for the proper weights to aggregate the sub-indicators.

In this section, we consider the composite indicators obtained applying the “direct BoD approach” as defined in Rogge (2018a):

$$M_{p,i}^w = M_p^w(I_i) = \begin{cases} \left(\sum_{j=1}^m \pi_{i,p,j} I_{i,j}^p \right)^{\frac{1}{p}}, & p \neq 0, \\ \prod_{j=1}^m I_{i,j}^{\pi_{i,0,j}}, & p = 0, \end{cases} \quad (28)$$

where for each unit i , $i = 1, 2, \dots, n$, the unit-dependent weight $\pi_{i,p,j}$, $j = 1, 2, \dots, m$, with $p \neq 0$ is the solution to the following problem:

$$\max_{\pi_{i,p,j}} \left(\sum_{j=1}^m \pi_{i,p,j} I_{i,j}^p \right)^{1/p}, \quad (29)$$

subject to the constraints:

$$\left(\sum_{j=1}^m \pi_{i,p,j} I_{i,j}^p \right)^{1/p} \leq 1, \quad c = 1, 2, \dots, n, \quad (30)$$

and

$$\pi_{i,p,j} \geq 0, \quad j = 1, 2, \dots, m. \quad (31)$$

The ratio of these weights is that each unit (i.e., country, region) tries to maximize its composite indicators (see Eq. (29)), to make the units’ composite indicators comparable in magnitude (see Eq. (30)) with non-negative weights (see Eq. (31)).

The case $p = 0$ is obtained numerically by choosing p close to zero (i.e., $p = 0.0001$). Results very close to $p = 0.0001$ are obtained by choosing $p = -0.0001$. The formulation of Problem (29)–(31) for $p = 0$ is still a challenge since the trivial solution $\pi_{p,i,j} = 0$, $i = 1, 2, \dots, n$, $j = 1, 2, \dots, m$ satisfies Problem (29)–(31) if the values of the sub-indicators fall in the interval $(0, 1]$. This is why, instead of solving problem (29)–(31) with $p = 0$, we prefer solve the problem with $p \neq 0$ small enough.

As in the previous experiment, we consider a grid of p -order, $p_l = -M + (2l - 1)$, $l = 1, 2, \dots, M$, so the p -orders considered are integer

Table 3
Average values (left panel) and third quartiles (right panel) of BoD weights for different p -orders.

Arithmetic means of BoD weights				Third quartiles of BoD weights			
p	$\pi_{i,p,1}$ (H)	$\pi_{i,p,2}$ (E)	$\pi_{i,p,3}$ (I)	p	$\pi_{i,p,1}$ (H)	$\pi_{i,p,2}$ (E)	$\pi_{i,p,3}$ (I)
-5	0.706	0.101	0.126	-5	0.992	0.071	0.000
-4	0.712	0.108	0.125	-4	0.994	0.082	0.000
-3	0.715	0.116	0.126	-3	0.995	0.093	0.000
-2	0.719	0.124	0.128	-2	0.997	0.106	0.000
-1	0.722	0.132	0.131	-1	0.998	0.121	0.000
0	0.721	0.150	0.129	0	1.000	0.324	0.000
1	0.723	0.163	0.131	1	1.002	0.360	0.000
2	0.726	0.175	0.133	2	1.003	0.399	0.000
3	0.730	0.189	0.134	3	1.005	0.443	0.000
4	0.734	0.204	0.135	4	1.006	0.490	0.000
5	0.738	0.220	0.136	5	1.008	0.543	0.000

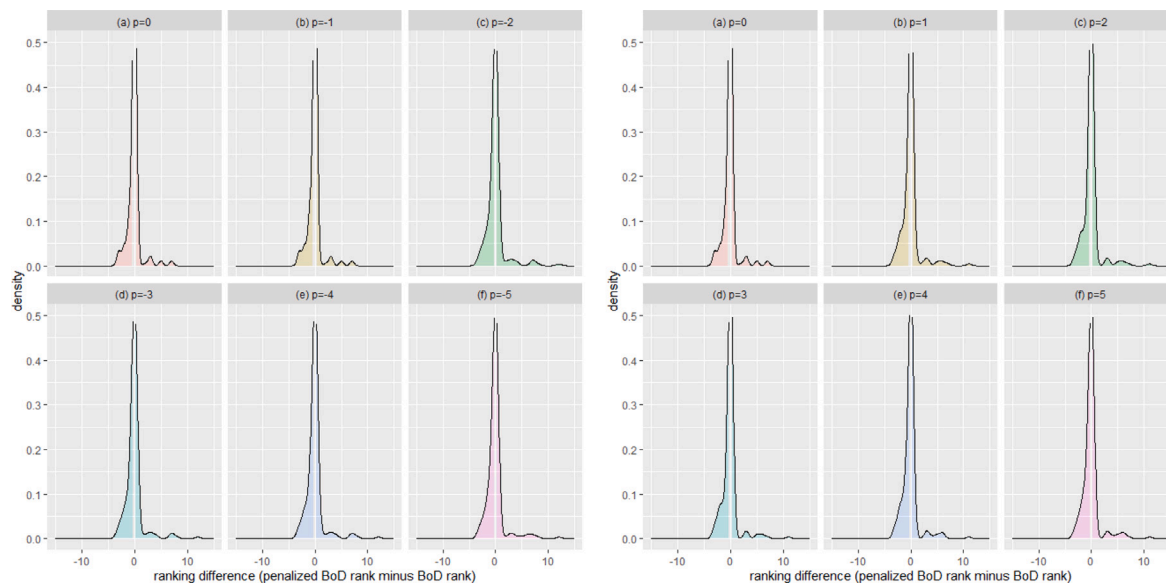


Fig. 3. Distribution of ranking difference $d_i(p) = r_{pBoD}(i, p) - r_{BoD}(i, p)$, $i = 1, 2, \dots, n$ (i.e., penalized BoD composite indicator of order p minus the corresponding BoD composite indicator of order p) for $p = -5, -4, -3, -2, -1, 0$ (left panel) $p = 0, 1, 2, 3, 4, 5$ (right panel).

values varying from $-M + 1$ to $M - 1$. We choose $M = 11$ since in the literature the p -value considered usually varies from -5 to 5 .

We solve Problem (29)–(31) for each value p_l , $l = 1, 2, \dots, 11$ and for each country/unit i , $i = 1, 2, \dots, n$. We therefore obtain the weights $\pi_{i,p,1}$, $\pi_{i,p,2}$, $\pi_{i,p,3}$ relative, respectively, to the three indicators mentioned above, i.e., Health (H), Education (E), and Income (I). Table 3 shows the average values (left panel) and third quartile (right panel) of the weight distribution $\pi_{i,p_l,j}$, $i = 1, 2, \dots, n$ corresponding to the three sub-indicators (i.e. $j = 1, 2, 3$) and the eleven values of the order p .

The left panel of Table 3 shows that the average values and third quartiles of the country-specific weights of the health dimension dominates for education and income for any $p = -5, -4, \dots, 4, 5$. The mean of the weights associated with health are constant with respect to p , while the mean associated with education increases slightly with p , and the same behavior can be seen in the third quartile of health and education. Interestingly, the mean of the weights associated with income slightly varies with p , but the third quartile is zero as a function of p . This implies that only a few units have weights different from zero, indicating that health and education play a more crucial role than income. Furthermore, the right panel of Table 3 shows that education plays a more relevant role when aggregative approaches with positive order p are used.

Recalling that, when a power mean of positive order is used as indicator, the marginal increase in the value of the indicator is much higher when the absolute value of the indicator is large (Rogge, 2018a),

we conclude that education especially affects the composite indicators that encourage the improvement of countries with good performance.

As in Section 4.1, we analyze the distribution of the ranking difference $d_i(p) = r_{pBoD}(i, p) - r_{BoD}(i, p)$, $i = 1, 2, \dots, n$, induced by the composite indicators defined by the penalized BoD and BoD direct approaches, respectively. Fig. 3 shows the distribution of $d_i(p)$, $i = 1, 2, \dots$ for negative values of p , $p = -5, -4, -3, -2, -1$ and $p = 0$ (left panel), and for positive p , $p = 1, 2, 3, 4, 5$ and $p = 0$ (right panel).

The distributions shown in Fig. 3 are not symmetric with negative skewness (i.e., $-2.931, -2.792, -2.812, -2.935, -2.826, -2.367, -3.442, -3.324, -3.298, -2.861, -2.876$). In line with the power mean (penalized and non-penalized) composite indicators, the penalized BoD provides smaller rankings than those from the non-penalized BoD indicators. A comparison between Fig. 3 and Fig. 1 shows that the standard deviations of the distributions of the BoD ranking differences (penalized minus non-penalized) are smaller than the standard deviations of the distributions of the power mean ranking differences (penalized minus non-penalized). The eleven standard deviations for p varying from -5 to 5 are about halved with respect to those of power mean approach; these are as follows: 1.424, 1.435, 1.429, 1.431, 1.364, 1.311, 1.452, 1.475, 1.501, 1.414, 1.419. This is an expected finding since the BoD weights are country-specific, thereby reducing the effect of the penalization. This finding, together with the results about the quartiles shown in the right panel of Table 3, leads to conclude that the concentration of weights in the dimensions of wealth and education reduces the

Table 4

The first twenty (top panel) and the last twenty (bottom panel) countries according to the power means (non penalized/penalized) and BoD direct country-specific weights (non-penalized/penalized) for $p = -1$ (HM), 0 (GM), 1 (AM). The rankings are obtained using three digits after the decimal.

Country	"Power-mean ranking"						"Benefit of the doubt ranking"					
	rHM	rGM	rAM	rPHM	rPGM	rPAM	rHM	rGM	rAM	rPHM	rPGM	PAM
Liechtenstein	21	19	19	23	23	21	1	1	1	1	1	1
Qatar	46	45	39	60	53	46	1	1	1	1	1	1
Ireland	2	2	2	2	2	2	1	1	1	5	4	3
Germany	5	6	6	5	5	5	1	1	1	8	5	4
Norway	1	1	1	1	1	1	1	1	1	8	5	4
Switzerland	2	2	2	3	3	2	1	1	1	5	7	4
Singapore	12	11	10	15	12	12	1	1	1	1	7	7
Australia	9	8	8	8	8	9	1	1	1	7	7	7
Iceland	4	4	5	4	4	4	1	1	1	8	7	7
Hong Kong	5	4	4	6	6	5	1	1	1	1	3	12
Japan	21	21	21	22	21	21	11	11	11	11	11	10
Luxembourg	24	22	20	24	24	24	11	11	11	11	11	10
New Zealand	15	15	15	14	15	15	11	11	11	13	13	13
Sweden	7	7	7	7	7	7	14	14	14	13	13	13
Finland	11	11	12	11	11	11	15	15	15	15	15	15
Netherlands	7	8	8	8	8	7	16	16	16	16	16	16
United Kingdom	13	13	13	12	12	13	17	17	17	18	18	18
United States	17	17	17	17	17	17	18	18	18	17	17	17
Denmark	10	10	10	10	10	10	19	19	19	20	20	20
Arab Emirates	32	31	30	34	33	32	20	20	20	19	19	19
Zimbabwe	150	150	152	147	148	149	170	170	170	170	170	170
Gambia	172	172	173	169	169	172	171	171	171	170	170	170
Benin	157	158	161	154	155	157	172	172	172	172	172	172
Burkina Faso	182	182	181	182	182	182	173	173	173	173	173	173
Burundi	185	185	185	184	184	186	173	173	173	173	173	173
Guinea	177	178	179	176	175	175	173	173	173	173	173	173
Angola	147	148	150	145	145	147	176	176	176	176	176	176
Togo	166	167	170	165	165	166	177	177	177	177	177	177
Mozambique	181	181	182	180	180	181	178	178	178	178	178	178
Congo	174	175	177	173	174	174	179	179	179	179	179	179
Cameroon	151	153	154	148	151	151	180	180	180	180	180	180
Mali	186	184	183	186	184	185	181	181	181	181	181	181
Côte d'Ivoire	160	162	162	156	157	160	182	182	182	182	182	182
Guinea-Bissau	173	175	180	170	170	173	183	183	183	183	183	183
Nigeria	158	161	164	153	153	158	184	184	184	184	184	184
South Sudan	184	186	186	183	183	184	185	185	185	185	185	185
Lesotho	163	165	168	158	159	162	186	186	186	186	186	186
Sierra Leone	180	182	183	175	178	179	187	187	187	187	187	187
Chad	188	188	188	187	188	188	188	188	188	188	188	188
Central African Republic	187	187	189	185	187	187	189	189	189	189	189	189

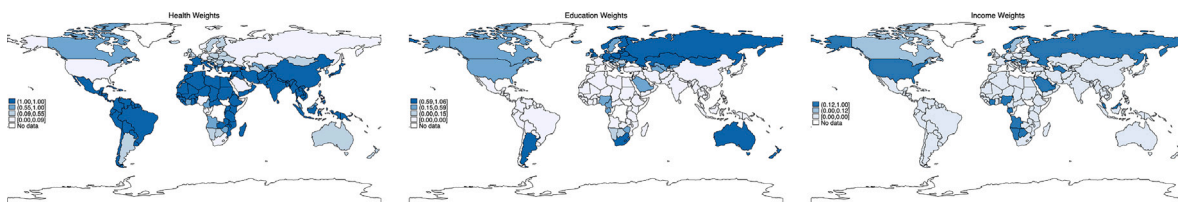


Fig. 4. Distribution of the BoD arithmetic mean weights across the globe. Health weights (left map), Education weights (middle map) and Income weights (right map).

variability among indicators and, as a consequence, reduces the effect of penalization.

Table 4 shows the first twenty (top panel) and the last twenty (bottom panel) countries according to the non-penalized arithmetic BoD ranking. Columns two to four contain the rank of non-penalized and penalized harmonic, geometric, and arithmetic means, respectively. Columns five to twelve contain the rank obtained with the penalized/non-penalized harmonic, geometric, and arithmetic BoD procedure. The rankings were obtained using three digits after the decimal.

Table 4 highlights two results. First, there are several units tied for first position in the BoD ranking, while the penalized one refines the ranking. Second, there is a great difference between the power mean

and direct BoD approaches mainly based on the fact that the indicator of several countries is constructed only with a weight different from zero. This is the case of Liechtenstein and Qatar, which have zero weights for health and education, while the weights are equal to one for income. To better investigate this point we use Fig. 4, which shows the distribution of the weights relative to health (left), education (middle), and income (right) across the globe. We can see that the weights of the African countries are very concentrated in one dimension, mainly health or, for the richest countries, income. The western countries have more diffused weights (dark gray in the panels of Fig. 4). The BoD and arithmetic mean rankings are rather close for the poorest countries where the values of education and income are very small, and they are

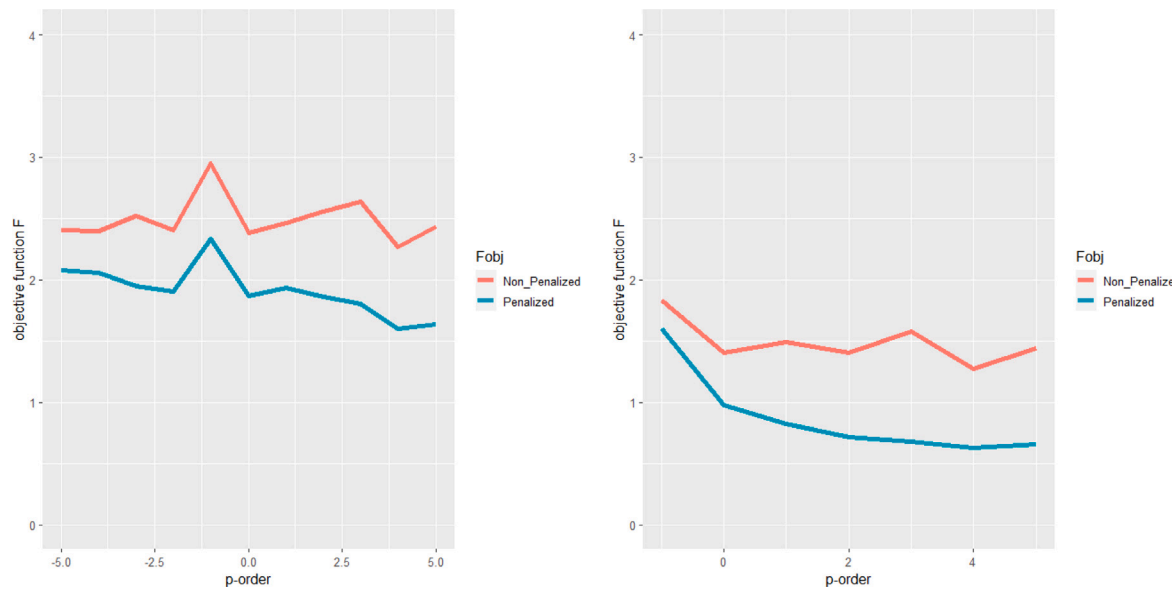


Fig. 5. Function F of Problem (27) when the BoD power mean and BoD penalized power mean are used to build the composite indicator and p varies from -5 to 5 (left panel) and from -1 to 5 (right panel).

Table 5

Spearman’s rank correlation between the power mean and BoD rankings. All correlations are significant with p -values less than 0.001 .

	rHM	rGM	rAM	rPHM	rPGM	rPAM
rBoD_HM	0.95	0.95	0.96	0.94	0.94	0.95
rBoD_GM	0.95	0.95	0.96	0.94	0.94	0.95
rBoD_AM	0.95	0.95	0.96	0.94	0.94	0.95
rBoD_PHM	0.95	0.95	0.96	0.93	0.94	0.95
rBoD_PGM	0.95	0.95	0.96	0.93	0.94	0.95
rBoD_PAM	0.95	0.95	0.96	0.93	0.94	0.95

also close for western countries where the weights are spread out. We continue to analyze the relationship between the BoD and power mean approaches using Spearman’s rank correlation.

Table 5 shows the values of the rank correlation between the composite indicators obtained with penalized and non-penalized power mean aggregation procedure and the penalized and non-penalized BoD aggregation procedure. We observe that the correlation coefficients reach the largest values for the correlation between the non-penalized arithmetic mean composite indicators and the indicators obtained with the BoD procedure.

We conclude this section by solving problem (27) to investigate whether the geometric mean also plays a crucial role in the BoD aggregation procedure.

Fig. 5 shows the graph of the objective function F of Problem (27) as a function of p when p varies from -5 to 5 (left panel) and from -1 to 5 (right panel) when the BoD approach is used. In contrast to the power mean aggregation, the curves are rather flat with the maximum value achieved by the non-penalized BoD. Interestingly, the penalized mean shows ranking difference magnitudes smaller than those of the non-penalized mean as observed in the case of power means. The results in Fig. 5 show that the ranking differences between the penalized and non-penalized BoD are negligible, especially when compared with the differences observed in Fig. 1. This confirms that the effect of the penalization is reduced by the choice of country-specific weights.

5. Conclusions

This paper proposes the penalized power means as an approach to constructing composite indicators that extends and supports the Mazziotta Pareto Index. The penalized mean accounts for the variability across indicators while continuing to satisfy some crucial properties already met by power means. More interestingly, the penalized approach provides composite indicators whose corresponding rankings are less sensitive to the choice of the p -order and more refined than the non-penalized ones. In fact, the penalization is able to discriminate units taking into account for their horizontal variability. The discriminatory power of the penalized means reduces when unit specific weights are considered. The choice of the parameter K is crucial for unit specific weights and it should be further investigated. In Appendix D we provide one simple choice. Our empirical analysis shows that the non-penalized/penalized geometric mean is the best choice for reducing ranking variations with respect to order p , since $p = 0$ is the “middle point” of the interval $p \in (-\infty, +\infty)$. This result can be explained for the non-penalized power mean by the monotonicity of the power means, and it seems to extend to the penalized power means as well.

Finally, the penalization proposed applies to other aggregation procedures such as the class of Benefit of the Doubt approaches. Extensions to the indirect BoD and Biggeri’s approaches deserve further investigation.

Moreover, it could be interesting to investigate how the correlations between indicators and the non-uniqueness issue of BoD weights impact on the ranking. The outcomes resulting from the comparison of the penalized power mean with both the BoD direct and penalized BoD direct approaches may be affected by the positive correlation among the sub-indicators of the HDI. These comparative findings could significantly differ if the sub-indicators exhibit negative or mixed correlations. These points deserve attention and will be the object of future study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Auxiliary results

Following Grünwald and Páles (2022), we recall the following technical lemma, which is useful for establishing Properties 11 and 12 in Proposition 3. The latter is a simplified version of Corollary 12 in Grünwald and Páles (2022) when $p_1(x) = p_2(x) = \dots = p_n(x) = p(x) = x^\alpha$ and $q_1(x) = q_2(x) = \dots = q_n(x) = q(x) = x^\beta$. For the reader's convenience, we outline the proof.

Lemma 1. Let $I \subset \mathbb{R}_+$, $n \geq 2$, $x_i \in I$, $i = 1, 2, \dots, n$. Let $\alpha, \beta \in \mathbb{R}$ such that $\beta \geq \alpha > 0$, then

$$\frac{\sum_{i=1}^n x_i^{\beta-1}}{\sum_{i=1}^n x_i^\beta} \leq \frac{\sum_{i=1}^n x_i^{\alpha-1}}{\sum_{i=1}^n x_i^\alpha}. \tag{32}$$

Proof of Lemma 1.

Let $\delta = \beta - \alpha \geq 0$. It is simple to prove that the following inequality holds:

$$t^\delta \left(1 - \frac{1}{t}\right) \geq \left(1 - \frac{1}{t}\right), \quad \forall t > 0. \tag{33}$$

For $x_1, x_2, \dots, x_n, y \in I$, choosing $t = x_i/y$ in (33), inequality (33) becomes

$$\left(\frac{x_i}{y}\right)^{\beta-\alpha} \left(1 - \frac{y}{x_i}\right) \geq \left(1 - \frac{y}{x_i}\right), \tag{34}$$

which also reads

$$\left(\frac{x_i}{y}\right)^\beta \left(1 - \frac{y}{x_i}\right) \geq \left(\frac{x_i}{y}\right)^\alpha \left(1 - \frac{y}{x_i}\right), \tag{35}$$

that is,

$$\left(\frac{1}{y}\right)^\beta (x_i^\beta - yx_i^{\beta-1}) \geq \left(\frac{1}{y}\right)^\alpha (x_i^\alpha - x_i^{\alpha-1}). \tag{36}$$

Summing (36) in $i \in \{1, 2, \dots, n\}$, we obtain

$$\left(\frac{1}{y}\right)^\beta \left(\sum_{i=1}^n x_i^\beta - y \sum_{i=1}^n x_i^{\beta-1}\right) \geq \left(\frac{1}{y}\right)^\alpha \left(\sum_{i=1}^n x_i^\alpha - \sum_{i=1}^n x_i^{\alpha-1}\right). \tag{37}$$

Choosing $y = \frac{\sum_{i=1}^n x_i^\alpha}{\sum_{i=1}^n x_i^{\alpha-1}}$ in the right side of (37) and simplifying $\left(\frac{1}{y}\right)^\beta$ yield

$$\left(\sum_{i=1}^n x_i^{\beta-1}\right) \left(\frac{\sum_{i=1}^n x_i^\beta}{\sum_{i=1}^n x_i^{\beta-1}} - y\right) \geq 0. \tag{38}$$

Thus, bearing in mind that y equals $\frac{\sum_{i=1}^n x_i^\alpha}{\sum_{i=1}^n x_i^{\alpha-1}}$, the inequality (38) reads

$$\left(\sum_{i=1}^n x_i^{\beta-1}\right) \left(\frac{\sum_{i=1}^n x_i^\beta}{\sum_{i=1}^n x_i^{\beta-1}} - \frac{\sum_{i=1}^n x_i^\alpha}{\sum_{i=1}^n x_i^{\alpha-1}}\right) \geq 0. \tag{39}$$

This concludes the proof. \square

Appendix B. Proofs of Proposition 2 and Proposition 3

Proof of Proposition 2

The derivative of $S_p^2(\underline{I} + \underline{c})$ with respect to c is

$$\frac{\partial \tilde{S}_p^2(\underline{I} + \underline{c})}{\partial c} = \frac{2K}{p} \frac{\left[\frac{1}{m} \sum_{j=1}^m (I_j + c)^{2p}\right]}{\left[\frac{1}{m} \sum_{j=1}^m (I_j + c)^p\right]^3} \times \left[\frac{\frac{1}{m} \sum_{j=1}^m (I_j + c)^{2p-1}}{\frac{1}{m} \sum_{j=1}^m (I_j + c)^{2p}} - \frac{\frac{1}{m} \sum_{j=1}^m (I_j + c)^{p-1}}{\frac{1}{m} \sum_{j=1}^m (I_j + c)^p} \right], \tag{40}$$

which also reads

$$\frac{\partial \tilde{S}_p^2(\underline{I} + \underline{c})}{\partial c} = \frac{2K}{p} \frac{\left[\frac{1}{m} \sum_{j=1}^m (I_j + c)^{2p}\right]}{\left[\frac{1}{m} \sum_{j=1}^m (I_j + c)^p\right]^3} H_p(c), \tag{41}$$

where $H_p(c)$ is given by

$$H_p(c) = \left[\frac{\frac{1}{m} \sum_{j=1}^m (I_j + c)^{2p-1}}{\frac{1}{m} \sum_{j=1}^m (I_j + c)^{2p}} - \frac{\frac{1}{m} \sum_{j=1}^m (I_j + c)^{p-1}}{\frac{1}{m} \sum_{j=1}^m (I_j + c)^p} \right]. \tag{42}$$

The sign of $\frac{\partial \tilde{S}_p^2(\underline{I} + \underline{c})}{\partial c}$ depends on $\frac{H_p(c)}{p}$. Applying Lemma 1 in Appendix A with $\beta = 2p$ and $\alpha = p$ when $p > 0$, we obtain $H_p(c) \leq 0$ and $\frac{H_p(c)}{p} \leq 0$. Choosing $\alpha = 2p$, $\beta = p$, when $p < 0$, we have $H_p(c) \geq 0$ and $\frac{H_p(c)}{p} \leq 0$. By virtue of Eq. (41), this implies that $\tilde{S}_p^2(\underline{I} + \underline{c})$ is a decreasing function of c .

This concludes the proof. \square

Proof of Proposition 3

Observing that $M_p(\underline{c}) = c$ and $\tilde{S}_p^2(\underline{c}) = 0 \forall p$, we have $PM_p^\pm(\underline{c}) = c$.

Since $\lim_{c \rightarrow 0} M_p(\underline{c}) = 0$ and $\lim_{c \rightarrow 0} \tilde{S}_p^2(\underline{c}) = 0$, Property 2 follows directly from (16).

Properties 3 and 4 follow easily, observing that $g_p^-(\underline{I}) \leq 1$, $g_p^+(\underline{I}) \geq 1$ and $g_p^\pm = 1$ if and only if $\tilde{S}_p^2(\underline{I}) = 0$.

The quantity $\tilde{S}_p^2(\underline{I})$ in (16) can be rewritten as follows:

$$\tilde{S}_p^2(\underline{I}) = \frac{K}{p^2} \frac{1}{m} \sum_{j=1}^m \left(\left(\frac{I_j}{M_p(\underline{I})} \right)^p - 1 \right)^2. \tag{43}$$

Taking the limit of (43) for $p \rightarrow -\infty$ and recalling that $M_p(\underline{I}) \xrightarrow{p \rightarrow -\infty} \min(I_1, I_2, \dots, I_m) \leq I_j$, $j = 1, 2, \dots, m$, we have

$$\lim_{p \rightarrow -\infty} p \tilde{S}_p^2(\underline{I}) = \lim_{p \rightarrow -\infty} \frac{1}{p} = 0^-. \tag{44}$$

Substituting (44) into (15) we prove Property 5.

Analogously, taking the limit of (43) for $p \rightarrow +\infty$ and recalling that

$$M_p(\underline{I}) \xrightarrow{p \rightarrow +\infty} \max(I_1, I_2, \dots, I_m) \geq I_j, \quad j = 1, 2, \dots, m, \text{ we obtain}$$

$$\lim_{p \rightarrow +\infty} p \tilde{S}_p^2(\underline{I}) = \lim_{p \rightarrow +\infty} \frac{1}{p} = 0^+. \tag{45}$$

Substituting (45) into (15), we obtain Property 6.

Taking the limit for $p \rightarrow 0$ of $g_p^\pm(\underline{I})$, we obtain

$$\begin{aligned} \lim_{p \rightarrow 0} g_p^\pm(\underline{I}) &= \lim_{p \rightarrow 0} \left(1 \pm p \tilde{S}_p^2(\underline{I}) \right)^{\frac{1}{p}} = \lim_{p \rightarrow 0} \exp \left\{ \frac{\ln \left(1 \pm p \tilde{S}_p^2(\underline{I}) \right)}{p} \right\} \\ &= \lim_{p \rightarrow 0} \exp \left\{ \tilde{S}_p^2(\underline{I}) \frac{\ln \left(1 \pm p \tilde{S}_p^2(\underline{I}) \right)}{p \tilde{S}_p^2(\underline{I})} \right\} \\ &= \exp \left\{ \lim_{p \rightarrow 0} \tilde{S}_p^2(\underline{I}) \frac{\ln \left(1 \pm p \tilde{S}_p^2(\underline{I}) \right)}{p \tilde{S}_p^2(\underline{I})} \right\} \end{aligned}$$

$$= \exp \{ \tilde{S}_0^2(I) \} \exp \left\{ \lim_{p \rightarrow 0} \frac{\ln \left(1 \pm p \tilde{S}_p^2(I) \right)}{p \tilde{S}_p^2(I)} \right\}, \tag{46}$$

and using the L'Hôpital's rule, we obtain

$$\lim_{p \rightarrow 0} g_p^\pm(I) = \exp \{ \pm \tilde{S}_0^2(I) \}. \tag{47}$$

This concludes the proof of Property 7.

Property 8 follows from Properties 3 and 6.

Property 9 follows from Properties 3 and 5.

Property 10 follows from the homogeneity property of the power means, observing that $g_p^\pm(c I) = g_p^\pm(I)$.

To prove Property 11 and 12, it is enough to prove that the penalization factor $g_p^-(I + c) \geq g_p^-(I)$ and $g_p^+(I + c) \leq g_p^+(I)$, for any $c \geq 0$.

Let $G_p^\pm(c) = g_p^\pm(I + c)$. The derivative of G_p^\pm with respect to c is

$$\frac{dG_p^\pm(c)}{dc} = \pm (G_p^\pm)^{1-p} \frac{\partial \tilde{S}_p^2(I + c)}{\partial c}. \tag{48}$$

The derivative of $\tilde{S}_p^2(I + c)$ with respect to c is non-positive as proven in Proposition 2. This concludes the proof of Properties 11 and 12.

Property 8 implies that $PM_p^-(I) \leq b$ for all choice of K in Definition 1, moreover, Property 1 implies that $PM_p^-(a) = a$, therefore it is always possible to find $K > 0$ such that $PM_p^-(I) \geq a$ for all $I \in [a, b]^m$. On the other hand, Property 9 implies that $PM_p^+(I) \geq a$ for all choice of K in Definition 1, moreover, Property 1 implies that $PM_p^+(b) = b$, therefore it is always possible to find $K > 0$ such that $PM_p^+(I) \leq b$ for all $I \in [a, b]^m$.

This concludes the proof of Property 13 and the proof of the Proposition. \square

Appendix C. Detailed ranking corresponding to the composite indicators of Sections 4.1 and 4.2

Table 6 and Table 7 show the country rankings according to harmonic (HM), geometric (GM), and arithmetic (AM) means and their penalized versions denoted with PHM, PGM, and PAM. The prefix r means rank.

Appendix D. Benefit of the Doubt aggregative approach with relative importance constraints

In this Appendix we analyze the effect of penalization on the composite indicators defined by the Benefit of the Doubt (BoD) direct approach (see, Rogge (2018a) and Rogge (2018b)) when relative importance constraints on the weights are imposed.

The composite indicators obtained applying the “direct BoD approach” with relative importance constraints are given by (28), where, for each unit $i, i = 1, 2, \dots, n$, the weights $\pi_{i,p,j}, j = 1, 2, \dots, m$, with $p \neq 0$ are determined as solution of optimization problem (29)–(31) with the addition of the following constraints (see Rogge (2018a)):

$$\frac{\pi_{i,p,j} I_{i,j}^p}{\sum_{s=1}^m \pi_{c,p,s} I_{c,s}^p} \geq 0.1, \quad c = 1, 2, \dots, n, \quad j = 1, 2, \dots, m. \tag{49}$$

The constraints (49) guarantee that each indicator has a relative contribution of at least 10%.

The case $p = 0$ is obtained numerically by choosing p close to zero (i.e., $p = 0.0001$). Results very close to $p = 0.0001$ are obtained by choosing $p = -0.0001$.

As done in Section 4, we solve Problem (29)–(31), (49) for each value $p_l = -M + (2l - 1), l = 1, 2, \dots, M$, with $M = 11$, and for each country/unit $i, i = 1, 2, \dots, n$. Here, the penalized power means are computed rescaling the quantities $\tilde{L}_{w,p,i}$, with $w = \pi$ and $p = p_l$, in (26) by choosing K as follows:

$$K = \frac{0.01}{\max_{\substack{i=1,2,\dots,n, \\ l=1,2,\dots,M}} \tilde{L}_{\pi,p_l,i}}. \tag{50}$$

This rescaling is necessary to make the loss of information $\tilde{S}_{w,p,i}^2$, with $w = \pi$ and $p = p_l$, comparable across different units $i, i = 1, 2, \dots, n$, and orders $p_l, l = 1, 2, \dots, M$. Note that, with the choice (50), the maximum value attained by the quantities $\tilde{S}_{w,p,i}^2$, with $w = \pi$ and $p = p_l$, is equal to 0.01. This is in line with the standardization process made by Mazziotta and Pareto, where the variance of the indicators is to 0.01 times its mean. Note that with this choice of K the penalized power means are range preserving.

Table 8 shows the average values (left panel) and third quartile (right panel) of the weight distribution $\pi_{i,p_l,j}, i = 1, 2, \dots, n$ corresponding to the three sub-indicators (i.e. $j = 1, 2, 3$) and the eleven values of the order p . We recall that $\pi_{i,p,1}, \pi_{i,p,2}, \pi_{i,p,3}$ are, respectively, the weights relative to the three indicators Health (H), Education (E), and Income (I).

Comparing Table 8 with Table 3 we can observe that, although the average values and third quartiles of the country-specific weights of the health dimension continue to dominate for education and income for any $p = -5, -4, \dots, 4, 5$, this dominance is weaker. Therefore, we can conclude that health and education play a more crucial role than income. Differently from the quartiles shown in Table 3, the third quartiles of income, although smaller than those of health and education, are not zero. This is the consequence of the relative importance constraints.

As done in Section 4, we analyze the distribution of the ranking difference $d_i(p) = r_{PBOD}(i, p) - r_{BOD}(i, p), i = 1, 2, \dots, n$, induced by the composite indicators defined by the penalized BoD and BoD direct approaches with relative importance constraints, respectively. Fig. 6 shows the distribution of $d_i(p), i = 1, 2, \dots$ for negative values of $p, p = -5, -4, -3, -2, -1$ and $p = 0$ (left panel), and for positive $p, p = 1, 2, 3, 4, 5$ and $p = 0$ (right panel).

The distributions shown in Fig. 6 are not symmetric with negative skewness except for $p = -3$ (i.e., $-0.066, -0.948, 0.728, -0.681, -0.273, -0.195, -1.737, -0.435, -1.773, -2.206, -1.830$, respectively, for p varying from -5 to 5). A comparison between Figs. 3 and 6 shows that the standard deviations of the distributions of the BoD ranking differences (penalized minus non-penalized) with relative importance constraints are smaller and more variable with respect to those of BoD approach for all values of p . The values of the standard deviations are as follows: 0.365, 0.505, 0.461, 0.417, 0.623, 0.696, 0.999, 0.768, 0.988, 1.085, 1.229. This means that the use of relative importance constraints contributes further to reduce the effect of penalization.

We conclude investigating the role of the geometric mean in the BoD aggregation procedure with relative importance constraints. To this end, we show in Fig. 7 the graph of the objective function F of Problem (27) as a function of p when p varies from -5 to 5 (left panel) and from -1 to 5 (right panel) when the BoD approach with relative importance constraints is used. Note that the addition of relative importance constraints to BoD approach makes the graph of function F more similar in size and shape to the function F associated with the power mean approach (see Fig. 2). Moreover, analogously to the power mean aggregation, the minimizer for both the functions shown in Fig. 7 is the middle point of the interval, i.e., $p = 0$ (left panel) and $p = 2$ (right panel).

Table 9 shows the first twenty (top panel) and the last twenty (bottom panel) countries according to the non penalized and penalized BoD with relative importance constraints.

To investigate the role of relative importance constraints, we compare the rankings obtained with the BoD without (Table 4) and with (Table 9) relative importance constraints. Note that, the rankings of Table 4 are obtained choosing $K = 1$. Nevertheless, the selection of K , as outlined in (50), yields identical rankings to those presented in Table 4. The comparison indicates that incorporating relative importance constraints into the BoD diminishes variations in rankings. This is likely due to the fact that the introduction of constraints reduces the admissible set of weights, and, as consequence, weakens the refining property of the penalization approach. This effect is more evident for $p = 0$ and $p = -1$.

Table 6

Country rankings, listed in alphabetical order, obtained with the power means (non penalized/penalized) and BoD direct country-specific weights (non-penalized/penalized). The method is “min” and three digits after the decimal are used to obtain the ranking.

Country	“Power-mean ranking”						“Benefit of the doubt ranking”					
	rHM	rGM (rHDI)	rAM	rPHM	rPGM	rPAM	rHM	rGM	rAM	rPHM	rPGM	PAM
Afghanistan	167	169	169	168	168	168	157	157	157	157	157	157
Albania	69	69	67	68	68	69	55	55	55	52	52	52
Algeria	91	91	91	93	92	91	72	72	72	71	71	71
Andorra	37	36	36	44	40	37	30	29	29	29	29	29
Angola	147	148	150	145	145	147	176	176	176	176	176	176
Antigua and Barbuda	80	78	74	82	80	80	68	68	68	68	68	68
Argentina	45	46	47	44	45	45	46	46	46	47	47	47
Armenia	77	81	81	73	75	78	90	90	90	90	90	90
Australia	9	8	8	8	8	9	1	1	1	7	7	7
Austria	18	18	18	18	18	18	29	29	29	31	31	31
Azerbaijan	86	88	89	85	85	86	108	108	108	108	108	108
Bahamas	57	57	59	57	57	57	67	67	67	67	67	67
Bahrain	42	41	41	43	42	41	45	45	45	45	45	45
Bangladesh	133	133	133	136	133	133	113	113	113	113	113	113
Barbados	57	59	59	58	59	59	47	47	47	46	46	46
Belarus	53	53	53	51	51	53	61	61	61	62	62	62
Belgium	13	13	13	13	14	13	25	25	25	25	27	27
Belize	112	111	107	113	114	112	95	95	95	95	95	95
Benin	157	158	161	154	155	157	172	172	172	172	172	172
Bhutan	130	129	129	132	131	129	121	121	121	120	120	120
Bolivia (Plurinational State of)	107	107	109	103	105	107	124	124	124	124	124	124
Bosnia and Herzegovina	76	73	74	75	75	76	64	64	64	64	64	64
Botswana	96	100	101	96	96	96	131	131	131	132	132	132
Brazil	84	84	84	83	83	84	83	83	83	83	83	83
Brunei Darussalam	47	47	46	53	51	47	27	27	27	25	25	25
Bulgaria	55	56	58	52	54	55	83	83	83	85	85	85
Burkina Faso	182	182	181	182	182	182	173	173	173	173	173	173
Burundi	185	185	185	184	184	186	173	173	173	173	173	173
Cabo Verde	126	126	127	126	126	126	108	108	108	108	108	108
Cambodia	144	144	143	146	146	144	134	134	134	134	134	134
Cameroon	151	153	154	148	151	151	180	180	180	180	180	180
Canada	16	16	16	15	16	16	22	22	21	22	22	22
Central African Republic	187	187	189	185	187	187	189	189	189	189	189	189
Chad	188	188	188	187	188	188	188	188	188	188	188	188
Chile	42	43	44	41	42	43	44	44	44	43	43	43
China	85	85	85	87	86	85	72	72	72	71	71	71
Colombia	83	83	83	84	83	83	65	65	65	65	65	65
Comoros	153	156	156	152	152	152	161	161	161	161	161	161
Congo	149	149	151	149	149	149	158	158	158	158	158	158
Congo (Democratic Republic of the)	174	175	177	173	174	174	179	179	179	179	179	179
Costa Rica	63	63	62	65	64	63	43	43	43	42	42	42
Croatia	44	44	45	40	42	44	52	52	52	55	55	55
Cuba	73	70	70	78	77	73	51	51	51	51	51	51
Cyprus	32	33	33	31	31	32	39	39	39	39	39	39
Czechia	26	27	27	25	26	26	36	36	36	36	36	36
Côte d'Ivoire	160	162	162	156	157	160	182	182	182	182	182	182
Denmark	10	10	10	10	10	10	19	19	19	20	20	20
Djibouti	169	166	159	178	172	167	147	147	147	147	147	147
Dominica	96	93	94	99	99	98	58	58	58	57	57	57
Dominican Republic	89	88	88	90	89	89	101	101	101	101	101	101
Ecuador	86	86	86	86	87	86	68	68	68	68	68	68
Egypt	115	116	115	116	116	115	120	120	120	119	119	119
El Salvador	124	124	123	124	124	124	106	106	106	105	105	105
Equatorial Guinea	146	145	145	149	147	145	141	141	141	141	141	141
Eritrea	183	180	176	188	186	183	152	152	152	152	152	152
Estonia	29	29	30	28	28	29	38	38	38	38	38	38
Eswatini (Kingdom of)	138	138	142	133	136	138	168	168	168	168	168	168
Ethiopia	177	173	172	179	179	178	151	151	151	151	151	151
Fiji	92	93	96	91	91	92	115	115	115	115	115	115
Finland	11	11	12	11	11	11	15	15	15	15	15	15
France	27	26	26	27	27	27	30	29	29	29	29	29
Gabon	117	119	119	114	115	116	140	140	140	140	140	140
Gambia	172	172	173	169	169	172	171	171	171	170	170	170
Georgia	57	61	63	56	57	57	48	48	48	48	48	48
Germany	5	6	6	5	5	5	1	1	1	8	5	4
Ghana	137	138	140	133	136	137	163	163	163	163	163	163
Greece	31	31	32	30	30	31	34	34	34	34	34	34
Grenada	71	74	78	69	70	71	104	104	104	104	104	104
Guatemala	127	127	125	130	129	127	99	99	99	99	99	99
Guinea	177	178	179	176	175	175	173	173	173	173	173	173
Guinea-Bissau	173	175	180	170	170	173	183	183	183	183	183	183

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Table 6 (continued).

Guyana	121	122	122	121	121	121	133	133	133	133	133	133
Haiti	167	170	171	167	167	168	165	165	165	165	165	165
Honduras	134	132	131	138	138	134	87	87	87	87	87	87
Hong Kong	5	4	4	6	6	5	1	1	1	1	3	12
Hungary	40	40	41	38	39	40	57	57	57	58	58	58
Iceland	4	4	5	4	4	4	1	1	1	8	7	7
India	130	130	130	129	130	131	135	135	135	135	135	135
Indonesia	107	107	107	107	105	107	122	122	122	122	122	122
Iran (Islamic Republic of)	70	71	71	71	71	70	75	75	75	74	74	74
Iraq	123	123	123	123	123	123	129	129	129	129	129	129
Ireland	2	2	2	2	2	2	1	1	1	5	4	3
Israel	19	19	21	19	19	19	21	21	21	22	22	22
Italy	30	29	29	32	31	30	25	25	25	22	22	22
Jamaica	100	101	100	97	98	100	96	96	96	96	96	96
Japan	21	21	21	22	21	21	11	11	11	11	11	10
Jordan	101	102	102	100	101	102	96	96	96	96	96	96
Kazakhstan	51	51	51	47	49	51	68	68	68	73	73	73
Kenya	142	143	143	139	140	142	150	150	150	150	150	150
Kiribati	132	134	134	131	132	132	141	141	141	141	141	141
Korea (Republic of)	23	24	24	21	21	23	28	28	28	28	28	28
Kuwait	67	64	56	75	69	66	32	32	32	32	32	32
Kyrgyzstan	120	120	120	120	120	120	117	117	117	117	117	117
Lao People's Democratic Republic	139	137	137	141	139	139	143	143	143	143	143	143
Latvia	36	37	38	36	36	36	41	41	41	41	41	41
Lebanon	96	92	90	102	100	96	49	49	49	48	48	48
Lesotho	163	165	168	158	159	162	186	186	186	186	186	186
Liberia	175	175	175	173	175	177	163	163	163	163	163	163
Libya	105	104	104	109	105	105	111	111	111	111	111	111
Liechtenstein	21	19	19	23	23	21	1	1	1	1	1	1
Lithuania	34	34	34	33	34	34	37	37	37	37	37	37
Luxembourg	24	22	20	24	24	24	11	11	11	11	11	10
Madagascar	165	163	162	166	166	165	149	149	149	149	149	149
Malawi	175	174	174	177	177	175	161	161	161	161	161	161
Malaysia	60	62	63	59	60	62	81	81	81	80	80	80
Maldives	101	95	91	114	109	101	49	49	49	48	48	48
Mali	186	184	183	186	184	185	181	181	181	181	181	181
Malta	28	28	28	29	28	28	32	32	32	32	32	32
Marshall Islands	119	117	115	119	119	118	101	101	101	101	101	101
Mauritania	161	157	156	163	162	161	156	156	156	156	156	156
Mauritius	65	66	66	63	64	65	87	87	87	87	87	87
Mexico	75	74	76	73	74	75	92	92	92	91	91	91
Micronesia (Federated States of)	136	136	136	133	134	136	143	143	143	143	143	143
Moldova (Republic of)	90	90	93	87	90	90	119	119	119	120	120	120
Mongolia	93	99	99	92	93	93	124	124	124	125	125	125
Montenegro	48	48	48	46	46	48	61	63	63	62	63	63
Morocco	122	121	121	122	122	122	75	75	75	74	74	74
Mozambique	181	181	182	180	180	181	178	178	178	178	178	178
Myanmar	148	147	146	151	149	148	147	147	147	147	147	147
Namibia	129	131	132	127	127	129	158	158	158	160	160	160
Nepal	143	142	140	143	143	143	128	128	128	128	128	128
Netherlands	7	8	8	8	8	7	16	16	16	16	16	16
New Zealand	15	15	15	14	15	15	11	11	11	13	13	13
Nicaragua	127	128	128	128	128	128	96	96	96	96	96	96
Niger	189	189	187	189	189	189	169	169	169	169	169	169
Nigeria	158	161	164	153	153	158	184	184	184	184	184	184
North Macedonia	82	82	82	79	80	82	85	85	85	84	84	84
Norway	1	1	1	1	1	1	1	1	1	8	5	4
Oman	60	59	59	62	60	59	59	59	59	59	59	59
Pakistan	156	154	152	161	159	154	146	146	146	146	146	146
Palau	50	50	50	47	47	50	52	52	52	53	53	53
Palestine	115	115	114	117	117	116	103	103	103	103	103	103
Panama	60	57	55	63	62	59	56	56	56	55	55	55
Papua New Guinea	154	155	154	155	154	152	160	160	160	159	159	159
Paraguay	103	103	103	101	102	103	99	99	99	99	99	99
Peru	79	79	78	77	77	79	75	75	75	74	74	74
Philippines	107	109	111	103	105	107	126	126	126	126	126	126
Poland	35	35	35	34	35	35	40	40	40	40	40	40
Portugal	37	38	37	38	38	38	35	35	35	35	35	35
Qatar	46	45	39	60	53	46	1	1	1	1	1	1
Romania	49	49	49	49	47	49	79	79	79	79	79	79
Russian Federation	52	52	52	49	50	52	74	74	74	78	78	78
Rwanda	162	160	158	162	163	163	139	139	139	139	139	139
Saint Kitts and Nevis	77	74	73	79	79	76	89	89	89	89	89	89
Saint Lucia	86	86	86	87	87	86	82	82	82	82	82	82
Saint Vincent and the Grenadines	93	98	98	95	95	93	114	114	114	114	114	114
Samoa	111	111	109	112	112	111	106	106	106	105	105	105

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Table 6 (continued).

Sao Tome and Principe	135	135	135	136	134	135	131	131	131	131	131	131
Saudi Arabia	41	41	41	41	41	41	42	42	42	43	43	43
Senegal	171	168	166	172	172	171	143	143	143	143	143	143
Serbia	64	64	65	60	63	63	80	80	80	80	80	80
Seychelles	66	67	67	66	66	67	91	91	91	92	92	92
Sierra Leone	180	182	183	175	178	179	187	187	187	187	187	187
Singapore	12	11	10	15	12	12	1	1	1	1	7	7
Slovakia	39	39	39	37	37	39	52	52	52	53	53	53
Slovenia	20	22	23	19	19	20	24	24	24	25	25	25
Solomon Islands	152	152	149	159	158	156	108	108	108	108	108	108
South Africa	113	114	118	109	111	113	136	136	136	136	136	136
South Sudan	184	186	186	183	183	184	185	185	185	185	185	185
Spain	25	25	25	26	25	25	23	23	23	21	21	21
Sri Lanka	71	72	71	72	73	71	68	68	68	68	68	68
Sudan	170	170	167	171	170	170	155	155	155	155	155	155
Suriname	93	95	97	94	94	93	122	122	122	122	122	122
Sweden	7	7	7	7	7	7	14	14	14	13	13	13
Switzerland	2	2	2	3	3	2	1	1	1	5	7	4
Syrian Arab Republic	154	151	147	160	161	155	112	112	112	112	112	112
Tajikistan	125	125	126	125	125	125	127	127	127	127	127	127
Tanzania	164	163	165	164	164	164	154	154	154	154	154	154
Thailand	81	79	76	81	80	81	66	66	66	66	66	66
Timor-Leste	141	141	139	142	142	141	137	137	137	136	136	136
Togo	166	167	170	165	165	166	177	177	177	177	177	177
Tonga	104	104	105	103	103	104	105	105	105	107	107	107
Trinidad and Tobago	67	67	69	66	66	68	94	94	94	94	94	94
Tunisia	96	95	95	97	97	98	75	75	75	74	74	74
Turkey	54	54	53	55	55	54	61	61	61	61	61	61
Turkmenistan	110	110	112	107	109	110	138	138	138	138	138	138
Uganda	159	158	160	156	156	159	167	167	167	167	167	167
Ukraine	73	74	78	70	71	73	92	92	92	92	92	92
United Arab Emirates	32	31	30	34	33	32	20	20	20	19	19	19
United Kingdom	13	13	13	12	12	13	17	17	17	18	18	18
United States	17	17	17	17	17	17	18	18	18	17	17	17
Uruguay	56	55	56	54	56	56	59	59	59	59	59	59
Uzbekistan	106	106	106	103	104	106	115	115	115	116	116	116
Vanuatu	140	140	138	140	140	140	130	130	130	130	130	130
Venezuela	113	113	113	111	113	113	118	118	118	117	117	117
Viet Nam	118	117	115	118	118	118	86	86	86	86	86	86
Yemen	179	179	177	181	181	180	153	153	153	153	153	153
Zambia	145	146	148	143	144	145	166	166	166	166	166	166
Zimbabwe	150	150	152	147	148	149	170	170	170	170	170	170

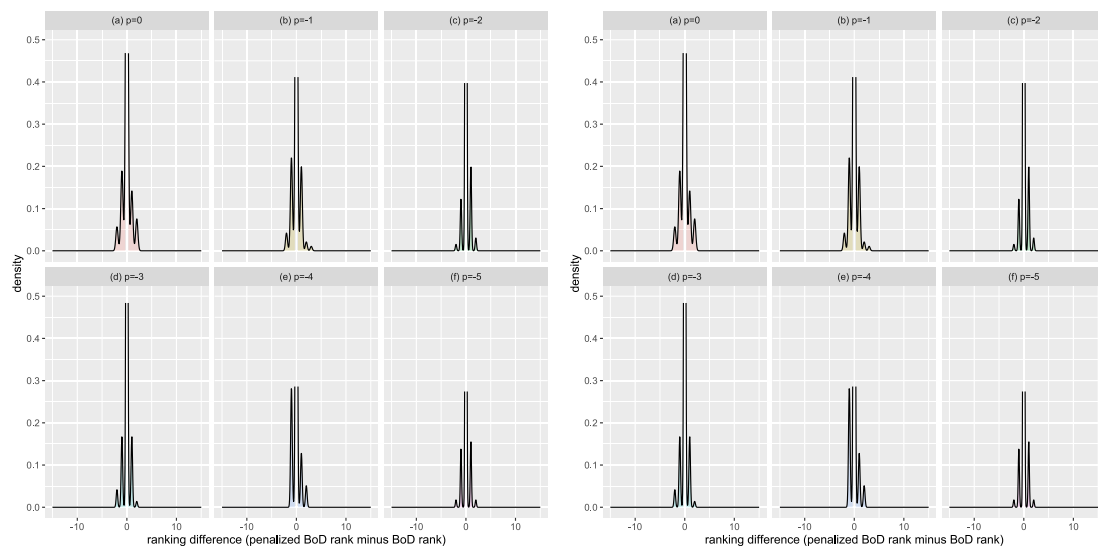


Fig. 6. Distribution of ranking difference $d_i(p) = r_{pBoD}(i, p) - r_{BoD}(i, p)$, $i = 1, 2, \dots, n$ (i.e., penalized BoD composite indicator of order p minus the corresponding BoD composite indicator of order p with relative importance constraints) for $p = -5, -4, -3, -2, -1, 0$ (left panel) $p = 0, 1, 2, 3, 4, 5$ (right panel).

Table 7

Country rankings obtained with the power means (non penalized/penalized) and BoD direct country-specific weights (non-penalized/penalized). The method is “min” and three digits after the decimal are used to obtain the ranking. The countries are ordered by HDI (rGM) rank.

Country	“Power-mean ranking”						“Benefit of the doubt ranking”					
	rHM	rGM (rHDI)	rAM	rPHM	rPGM	rPAM	rHM	rGM	rAM	rPHM	rPGM	PAM
Norway	1	1	1	1	1	1	1	1	1	8	5	4
Ireland	2	2	2	2	2	2	1	1	1	5	4	3
Switzerland	2	2	2	3	3	2	1	1	1	5	7	4
Hong Kong	5	4	4	6	6	5	1	1	1	1	3	12
Iceland	4	4	5	4	4	4	1	1	1	8	7	7
Germany	5	6	6	5	5	5	1	1	1	8	5	4
Sweden	7	7	7	7	7	7	14	14	14	13	13	13
Australia	9	8	8	8	8	9	1	1	1	7	7	7
Netherlands	7	8	8	8	8	7	16	16	16	16	16	16
Denmark	10	10	10	10	10	10	19	19	19	20	20	20
Finland	11	11	12	11	11	11	15	15	15	15	15	15
Singapore	12	11	10	15	12	12	1	1	1	1	7	7
Belgium	13	13	13	13	14	13	25	25	25	25	27	27
United Kingdom	13	13	13	12	12	13	17	17	17	18	18	18
New Zealand	15	15	15	14	15	15	11	11	11	13	13	13
Canada	16	16	16	15	16	16	22	22	21	22	22	22
United States	17	17	17	17	17	17	18	18	18	17	17	17
Austria	18	18	18	18	18	18	29	29	29	31	31	31
Israel	19	19	21	19	19	19	21	21	21	22	22	22
Liechtenstein	21	19	19	23	23	21	1	1	1	1	1	1
Japan	21	21	21	22	21	21	11	11	11	11	11	10
Luxembourg	24	22	20	24	24	24	11	11	11	11	11	10
Slovenia	20	22	23	19	19	20	24	24	24	25	25	25
Korea (Republic of)	23	24	24	21	21	23	28	28	28	28	28	28
Spain	25	25	25	26	25	25	23	23	23	21	21	21
France	27	26	26	27	27	27	30	29	29	29	29	29
Czechia	26	27	27	25	26	26	36	36	36	36	36	36
Malta	28	28	28	29	28	28	32	32	32	32	32	32
Estonia	29	29	30	28	28	29	38	38	38	38	38	38
Italy	30	29	29	32	31	30	25	25	25	22	22	22
Greece	31	31	32	30	30	31	34	34	34	34	34	34
United Arab Emirates	32	31	30	34	33	32	20	20	20	19	19	19
Cyprus	32	33	33	31	31	32	39	39	39	39	39	39
Lithuania	34	34	34	33	34	34	37	37	37	37	37	37
Poland	35	35	35	34	35	35	40	40	40	40	40	40
Andorra	37	36	36	44	40	37	30	29	29	29	29	29
Latvia	36	37	38	36	36	36	41	41	41	41	41	41
Portugal	37	38	37	38	38	38	35	35	35	35	35	35
Slovakia	39	39	39	37	37	39	52	52	52	53	53	53
Hungary	40	40	41	38	39	40	57	57	57	58	58	58
Bahrain	42	41	41	43	42	41	45	45	45	45	45	45
Saudi Arabia	41	41	41	41	41	41	42	42	42	43	43	43
Chile	42	43	44	41	42	43	44	44	44	43	43	43
Croatia	44	44	45	40	42	44	52	52	52	55	55	55
Qatar	46	45	39	60	53	46	1	1	1	1	1	1
Argentina	45	46	47	44	45	45	46	46	46	47	47	47
Brunei Darussalam	47	47	46	53	51	47	27	27	27	25	25	25
Montenegro	48	48	48	46	46	48	61	63	63	62	63	63
Romania	49	49	49	49	47	49	79	79	79	79	79	79
Palau	50	50	50	47	47	50	52	52	52	53	53	53
Kazakhstan	51	51	51	47	49	51	68	68	68	73	73	73
Russian Federation	52	52	52	49	50	52	74	74	74	78	78	78
Belarus	53	53	53	51	51	53	61	61	61	62	62	62
Turkey	54	54	53	55	55	54	61	61	61	61	61	61
Uruguay	56	55	56	54	56	56	59	59	59	59	59	59
Bulgaria	55	56	58	52	54	55	83	83	83	85	85	85
Bahamas	57	57	59	57	57	57	67	67	67	67	67	67
Panama	60	57	55	63	62	59	56	56	56	55	55	55
Barbados	57	59	59	58	59	59	47	47	47	46	46	46
Oman	60	59	59	62	60	59	59	59	59	59	59	59
Georgia	57	61	63	56	57	57	48	48	48	48	48	48
Malaysia	60	62	63	59	60	62	81	81	81	80	80	80
Costa Rica	63	63	62	65	64	63	43	43	43	42	42	42
Kuwait	67	64	56	75	69	66	32	32	32	32	32	32
Serbia	64	64	65	60	63	63	80	80	80	80	80	80
Mauritius	65	66	66	63	64	65	87	87	87	87	87	87
Seychelles	66	67	67	66	66	67	91	91	91	92	92	92
Trinidad and Tobago	67	67	69	66	66	68	94	94	94	94	94	94
Albania	69	69	67	68	68	69	55	55	55	52	52	52
Cuba	73	70	70	78	77	73	51	51	51	51	51	51

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Table 7 (continued).

Iran (Islamic Republic of)	70	71	71	71	71	70	75	75	75	74	74	74
Sri Lanka	71	72	71	72	73	71	68	68	68	68	68	68
Bosnia and Herzegovina	76	73	74	75	75	76	64	64	64	64	64	64
Grenada	71	74	78	69	70	71	104	104	104	104	104	104
Mexico	75	74	76	73	74	75	92	92	92	91	91	91
Saint Kitts and Nevis	77	74	73	79	79	76	89	89	89	89	89	89
Ukraine	73	74	78	70	71	73	92	92	92	92	92	92
Antigua and Barbuda	80	78	74	82	80	80	68	68	68	68	68	68
Peru	79	79	78	77	77	79	75	75	75	74	74	74
Thailand	81	79	76	81	80	81	66	66	66	66	66	66
Armenia	77	81	81	73	75	78	90	90	90	90	90	90
North Macedonia	82	82	82	79	80	82	85	85	85	84	84	84
Colombia	83	83	83	84	83	83	65	65	65	65	65	65
Brazil	84	84	84	83	83	84	83	83	83	83	83	83
China	85	85	85	87	86	85	72	72	72	71	71	71
Ecuador	86	86	86	86	87	86	68	68	68	68	68	68
Saint Lucia	86	86	86	87	87	86	82	82	82	82	82	82
Azerbaijan	86	88	89	85	85	86	108	108	108	108	108	108
Dominican Republic	89	88	88	90	89	89	101	101	101	101	101	101
Moldova (Republic of)	90	90	93	87	90	90	119	119	119	120	120	120
Algeria	91	91	91	93	92	91	72	72	72	71	71	71
Lebanon	96	92	90	102	100	96	49	49	49	48	48	48
Dominica	96	93	94	99	99	98	58	58	58	57	57	57
Fiji	92	93	96	91	91	92	115	115	115	115	115	115
Maldives	101	95	91	114	109	101	49	49	49	48	48	48
Suriname	93	95	97	94	94	93	122	122	122	122	122	122
Tunisia	96	95	95	97	97	98	75	75	75	74	74	74
Saint Vincent and the Grenadines	93	98	98	95	95	93	114	114	114	114	114	114
Mongolia	93	99	99	92	93	93	124	124	124	125	125	125
Botswana	96	100	101	96	96	96	131	131	131	132	132	132
Jamaica	100	101	100	97	98	100	96	96	96	96	96	96
Jordan	101	102	102	100	101	102	96	96	96	96	96	96
Paraguay	103	103	103	101	102	103	99	99	99	99	99	99
Libya	105	104	104	109	105	105	111	111	111	111	111	111
Tonga	104	104	105	103	103	104	105	105	105	107	107	107
Uzbekistan	106	106	106	103	104	106	115	115	115	116	116	116
Bolivia (Plurinational State of)	107	107	109	103	105	107	124	124	124	124	124	124
Indonesia	107	107	107	107	105	107	122	122	122	122	122	122
Philippines	107	109	111	103	105	107	126	126	126	126	126	126
Turkmenistan	110	110	112	107	109	110	138	138	138	138	138	138
Belize	112	111	107	113	114	112	95	95	95	95	95	95
Samoa	111	111	109	112	112	111	106	106	106	105	105	105
Venezuela (Bolivarian Republic of)	113	113	113	111	113	113	118	118	118	117	117	117
South Africa	113	114	118	109	111	113	136	136	136	136	136	136
Palestine	115	115	114	117	117	116	103	103	103	103	103	103
Egypt	115	116	115	116	116	115	120	120	120	119	119	119
Marshall Islands	119	117	115	119	119	118	101	101	101	101	101	101
Viet Nam	118	117	115	118	118	118	86	86	86	86	86	86
Gabon	117	119	119	114	115	116	140	140	140	140	140	140
Kyrgyzstan	120	120	120	120	120	120	117	117	117	117	117	117
Morocco	122	121	121	122	122	122	75	75	75	74	74	74
Guyana	121	122	122	121	121	121	133	133	133	133	133	133
Iraq	123	123	123	123	123	123	129	129	129	129	129	129
El Salvador	124	124	123	124	124	124	106	106	106	105	105	105
Tajikistan	125	125	126	125	125	125	127	127	127	127	127	127
Cabo Verde	126	126	127	126	126	126	108	108	108	108	108	108
Guatemala	127	127	125	130	129	127	99	99	99	99	99	99
Nicaragua	127	128	128	128	128	128	96	96	96	96	96	96
Bhutan	130	129	129	132	131	129	121	121	121	120	120	120
India	130	130	130	129	130	131	135	135	135	135	135	135
Namibia	129	131	132	127	127	129	158	158	158	160	160	160
Honduras	134	132	131	138	138	134	87	87	87	87	87	87
Bangladesh	133	133	133	136	133	133	113	113	113	113	113	113
Kiribati	132	134	134	131	132	132	141	141	141	141	141	141
Sao Tome and Principe	135	135	135	136	134	135	131	131	131	131	131	131
Micronesia (Federated States of)	136	136	136	133	134	136	143	143	143	143	143	143
Lao People's Democratic Republic	139	137	137	141	139	139	143	143	143	143	143	143
Eswatini (Kingdom of)	138	138	142	133	136	138	168	168	168	168	168	168
Ghana	137	138	140	133	136	137	163	163	163	163	163	163
Vanuatu	140	140	138	140	140	140	130	130	130	130	130	130
Timor-Leste	141	141	139	142	142	141	137	137	137	136	136	136
Nepal	143	142	140	143	143	143	128	128	128	128	128	128
Kenya	142	143	143	139	140	142	150	150	150	150	150	150
Cambodia	144	144	143	146	146	144	134	134	134	134	134	134
Equatorial Guinea	146	145	145	149	147	145	141	141	141	141	141	141

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Table 7 (continued).

Zambia	145	146	148	143	144	145	166	166	166	166	166	166
Myanmar	148	147	146	151	149	148	147	147	147	147	147	147
Angola	147	148	150	145	145	147	176	176	176	176	176	176
Congo	149	149	151	149	149	149	158	158	158	158	158	158
Zimbabwe	150	150	152	147	148	149	170	170	170	170	170	170
Syrian Arab Republic	154	151	147	160	161	155	112	112	112	112	112	112
Solomon Islands	152	152	149	159	158	156	108	108	108	108	108	108
Cameroon	151	153	154	148	151	151	180	180	180	180	180	180
Pakistan	156	154	152	161	159	154	146	146	146	146	146	146
Papua New Guinea	154	155	154	155	154	152	160	160	160	159	159	159
Comoros	153	156	156	152	152	152	161	161	161	161	161	161
Mauritania	161	157	156	163	162	161	156	156	156	156	156	156
Benin	157	158	161	154	155	157	172	172	172	172	172	172
Uganda	159	158	160	156	156	159	167	167	167	167	167	167
Rwanda	162	160	158	162	163	163	139	139	139	139	139	139
Nigeria	158	161	164	153	153	158	184	184	184	184	184	184
Côte d'Ivoire	160	162	162	156	157	160	182	182	182	182	182	182
Madagascar	165	163	162	166	166	165	149	149	149	149	149	149
Tanzania (United Republic of)	164	163	165	164	164	164	154	154	154	154	154	154
Lesotho	163	165	168	158	159	162	186	186	186	186	186	186
Djibouti	169	166	159	178	172	167	147	147	147	147	147	147
Togo	166	167	170	165	165	166	177	177	177	177	177	177
Senegal	171	168	166	172	172	171	143	143	143	143	143	143
Afghanistan	167	169	169	168	168	168	157	157	157	157	157	157
Haiti	167	170	171	167	167	168	165	165	165	165	165	165
Sudan	170	170	167	171	170	170	155	155	155	155	155	155
Gambia	172	172	173	169	169	172	171	171	171	170	170	170
Ethiopia	177	173	172	179	179	178	151	151	151	151	151	151
Malawi	175	174	174	177	177	175	161	161	161	161	161	161
Congo (Democratic Republic of the)	174	175	177	173	174	174	179	179	179	179	179	179
Guinea-Bissau	173	175	180	170	170	173	183	183	183	183	183	183
Liberia	175	175	175	173	175	177	163	163	163	163	163	163
Guinea	177	178	179	176	175	175	173	173	173	173	173	173
Yemen	179	179	177	181	181	180	153	153	153	153	153	153
Eritrea	183	180	176	188	186	183	152	152	152	152	152	152
Mozambique	181	181	182	180	180	181	178	178	178	178	178	178
Burkina Faso	182	182	181	182	182	182	173	173	173	173	173	173
Sierra Leone	180	182	183	175	178	179	187	187	187	187	187	187
Mali	186	184	183	186	184	185	181	181	181	181	181	181
Burundi	185	185	185	184	184	186	173	173	173	173	173	173
South Sudan	184	186	186	183	183	184	185	185	185	185	185	185
Central African Republic	187	187	189	185	187	187	189	189	189	189	189	189
Chad	188	188	188	187	188	188	188	188	188	188	188	188
Niger	189	189	187	189	189	189	169	169	169	169	169	169

Table 8

Average values (left panel) and third quartiles (right panel) of BoD weights for different p -orders with relative importance constraints.

Arithmetic means of BoD weights				Third quartiles of BoD weights			
p	$\pi_{i,p,1}$ (H)	$\pi_{i,p,2}$ (E)	$\pi_{i,p,3}$ (I)	p	$\pi_{i,p,1}$ (H)	$\pi_{i,p,2}$ (E)	$\pi_{i,p,3}$ (I)
-5	0.536	0.156	0.172	-5	0.720	0.200	0.090
-4	0.551	0.164	0.177	-4	0.738	0.224	0.092
-3	0.565	0.172	0.183	-3	0.755	0.251	0.094
-2	0.582	0.178	0.187	-2	0.771	0.130	0.096
-1	0.596	0.187	0.190	-1	0.786	0.142	0.098
0	0.604	0.197	0.200	0	0.800	0.155	0.100
1	0.617	0.207	0.202	1	0.813	0.170	0.106
2	0.628	0.219	0.205	2	0.825	0.187	0.112
3	0.635	0.237	0.208	3	0.836	0.205	0.118
4	0.646	0.253	0.209	4	0.847	0.436	0.125
5	0.657	0.270	0.210	5	0.857	0.554	0.132

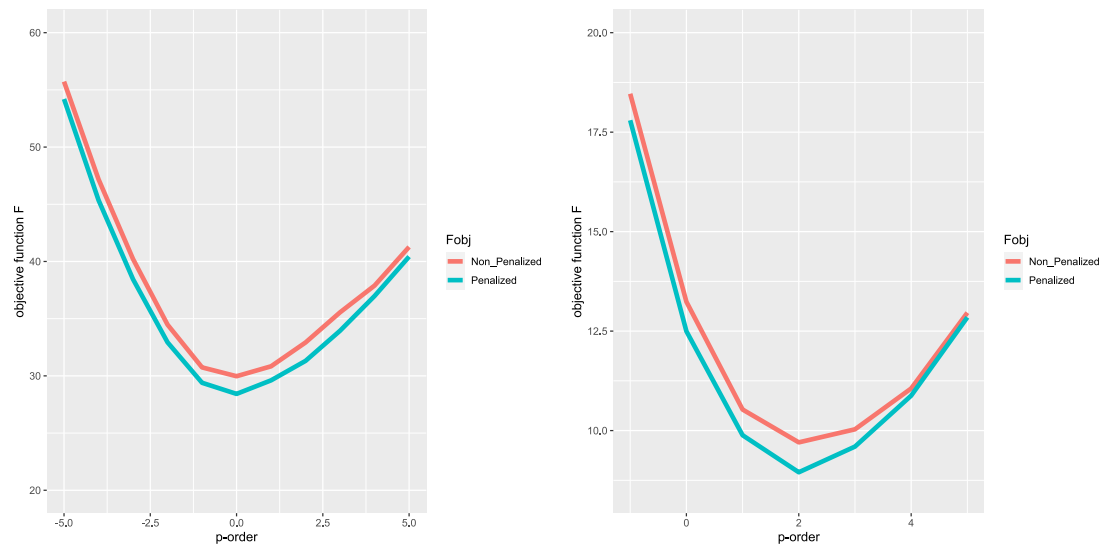


Fig. 7. Function F of Problem (27) when the BoD power mean and BoD penalized power mean with relative importance constraints are used to build the composite indicator and p varies from -5 to 5 (left panel) and from -1 to 5 (right panel).

Table 9

The first twenty (top panel) and the last twenty (bottom panel) countries according to the BoD direct country-specific weights with relative importance constraints (non-penalized/penalized) for $p = -1$ (HM), 0 (GM), 1 (AM). The rankings are obtained using three digits after the decimal.

Country	"BoD ranking"					
	rHM	rGM	rAM	rPHM	rPGM	rPAM
Hong Kong	1	1	1	1	1	1
Ireland	1	1	1	1	1	1
Norway	1	1	1	1	1	1
Singapore	1	1	1	1	1	1
Switzerland	1	1	1	1	1	1
Australia	1	1	1	1	1	6
Germany	1	1	1	1	1	6
Iceland	1	1	1	1	1	6
Sweden	9	9	9	9	9	9
Liechtenstein	9	9	9	10	9	9
Luxembourg	14	11	11	14	11	11
Finland	11	11	12	11	11	11
Netherlands	11	11	12	11	11	13
New Zealand	11	11	12	11	11	13
Japan	15	15	15	15	15	15
United Kingdom	15	16	16	15	16	16
Denmark	17	17	17	17	16	16
United States	18	18	18	18	18	18
Canada	19	19	19	19	19	19
Belgium	20	20	20	20	20	20
Angola	164	168	170	163	168	170
Benin	167	170	171	167	170	171
Gambia	173	172	172	173	172	172
Togo	173	174	173	172	174	173
Cameroon	171	173	174	170	172	174
Guinea	176	175	175	177	175	175
Burkina Faso	179	178	176	180	179	176
Congo	178	176	177	178	177	177
Burundi	181	181	178	183	181	178
Niger	185	182	178	185	182	179
Mozambique	179	180	180	179	180	181
Côte d'Ivoire	175	176	181	175	176	179
Nigeria	176	179	182	176	178	182
Mali	184	185	183	184	185	183
Guinea-Bissau	182	183	184	182	183	183
Lesotho	182	184	185	181	184	185
South Sudan	186	186	186	186	186	186
Sierra Leone	187	187	187	187	187	187
Chad	188	188	188	188	188	188
Central African Republic	189	189	189	189	189	189

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