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Assessment of OECD Better Life Index by incorporating public opinion

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ABSTRACT

Well-being has a multidimensional nature as it depends on multifaceted factors such as material conditions and quality of life. The Organization for Economic Co-operation and Development (OECD) has developed the Better Life Index (BLI) as part of the OECD Better Life initiative to facilitate the better understanding of what drives well-being of people. The BLI is a three-level hierarchical composite indicator that covers several socio-economic aspects. In this paper, considering the entire hierarchical structure of the index, we introduce a bottom-up procedure for the aggregation of the components at each level. We formulate the assessment of BLI as a multiple objective programming (MOP) problem that facilitates the implementation of different concepts to derive different aggregation schemes. We incorporate the data from previous years into the normalization process of the indicators, to take into account the discrepancy on their observed values and smooth their deviations across the years. Also, we consider the public opinion about well-being that is captured from the worldwide responses in the web platform of OECD BLI. We incorporate the public opinion into the assessment models in the form of weight restrictions. In this way, we reduce the effect of compensation that might be imposed by the adopted modelling approach. We apply our methodology to the data of 38 countries (35 OECD and 3 non-OECD economies) for the year 2017. Our findings illustrate that the public opinion in the form of weight restrictions can effectively drive the optimization process and depict the collective preferences to the BLI scores.

1. Introduction

While human societies evolve rapidly, dramatic changes occur in main aspects such as economy, politics, education and environment. As it is observed, economic growth is not always followed by other societal aspects, nor it is equally shared and beneficial to all parts of societies. However, the quality of life is more important than income. Hence, to obtain a better picture of how society is doing, it is crucial to go beyond the ordinary income-based measures (e.g. gross domestic product-GDP) that are inadequate to capture the societal progress and shift the awareness to more comprehensive measures that incorporate multi-faceted human-centric criteria. This necessity is officially manifested by influential and Nobel Laureates economists, such as J. Stiglitz, A. Sen and K. Arrow, in the report of the Commission on the Measurement of Economic Performance and Social Progress [1] initiated by the French Government in 2008. In sum, the recommendation of the report was that a wide range of socio-economic aspects, such as material conditions, quality of life and sustainability, should be considered for measuring well-being. In this respect, it is of outmost importance to create and monitor representative indicators that reflect sufficiently how well we perform in all areas and unveil if we are in the path of the coveted prosperity (well-being).

On this basis, the Organization for Economic Co-operation and Development (OECD) launched the OECD Better Life initiative [2,3] with the aim to develop better well-being metrics, to facilitate the better understanding of what drives well-being of people and guide the policy-makers to achieve greater progress for the common good. The initiative provides regular monitoring and benchmarking through the biennial "*How's Life?*" report [2,4,5] and [6] and the interactive web platform[1] that promotes the OECD Better Life Index (BLI). The OECD BLI covers several socio-economic aspects by incorporating eleven key topics (factors) that the OECD has identified as essential to well-being in terms of material living conditions and quality of life. Each topic is composed by one to four indicators. The BLI has a hierarchical structure with three levels. In a bottom-up representation, the first (bottom) level comprises of the indicators that form the eleven topics of the second level, which subsequently form the BLI at the third level. The web application is designed to inform people and raise the debate on

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[1] The OECD Better Life Index web platform http://www.oecdbetterlifeindex.org.

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measuring the well-being, as well as to encourage them to share their views about the topics that matter most to them. The public participation is critical considering the varying needs and the unequal distribution of the well-being outcomes among different regions and groups of the population. Also, the public opinion allows to focus on how life is lived, hence it should be taken into account when creating well-being measures and policies.

The multidimensional nature of well-being renders its measurement a rough task, which requires computational methods adequate to capture the several aspects involved. The Human Development Index (HDI) of United Nations is a composite index (see Refs. [7–9]) that is widely used as a proxy of well-being, however is confined only to income, education and health factors. On the other hand, it is challenging to synthesize the multifaceted components of BLI to obtain a single measure of well-being. This measure should provide concise results that are easy to interpret, as well as it should accommodate the comparison among countries and the conduct of assessment exercises. The OECD Handbook for the construction of composite indices [10] provides directives and methodological tools. However, there is still a great debate about the aggregation techniques that should be adopted since they will most likely manipulate the results. For example, in the case of using composite indices for assessment exercises in policy making, poor performance can be mostly attributed to the aggregation method that is adopted. Thus, it is difficult to reach a consensus about the appropriate aggregation technique for the construction of composite indices [11].

It is naive and arbitrary to consider that the eleven topics of BLI are of equal importance, i.e. that people believe that each topic has the same impact in their life. Assuming equal weights for the construction of composite indices has justifiably faced criticism since it implies equal worth and contribution of the included topics. Furthermore, if two topics are proved to be highly correlated, an equal weighting aggregation scheme causes a double counting [12]. An alternative to the equal or fixed weighting procedure is the *Benefit of the Doubt* (BoD) approach, which is based on Data Envelopment Analysis (DEA) [13]. The BoD approach [14,15], is a popular approach for constructing composite indices where the weights derive endogenously from the optimization process. The BoD approach estimates different weights for each unit under assessment in its most favorable way so as to reach the highest possible performance. Rogge [16] explored various weighted average functions in a BoD framework for the construction of composite indices. Zhu [17] noted that "*the notion of the quality of life is about a finite set of measurable attributes that can be weighted by some metric*" and employed DEA to derive a measure for the quality of life for the Fortune magazine's 20 best cities. Bernini et al. [18] proposed a new subjective well-being indicator based on residents' satisfaction of environment and community, personal life and leisure activities. The aggregation procedure employs the BoD approach with common weights for all the assessed countries.

The OECD has not adopted, so far, an aggregation approach for the case of BLI. It is left to the citizens though to create the BLI based on their views. This is explicitly declared in the BLI's website: "*Your Better Life Index is designed to let you, the user, investigate how each of the 11 topics can contribute to well-being*". However, this deliberate omission has stimulated the research about the construction of BLI. Mizobuchi [19] applied the BoD approach to construct the BLI for 34 countries (32 OECD members, Brazil and Russia) for the data of year 2011. The BoD was applied for the aggregation of the eleven topics (level 2), whose scores were estimated by the original averaging formula proposed by the OECD BLI initiative.[2] The obtained BLI scores were used to further investigate the link between the countries' well-being and the economic development, as reflected by per capita GDP. However, the approach of Mizobuchi [19] generates country-specific weights that maximize the performance (composite indicator) of each country, failing in this way to provide a common basis for comparisons among the countries. Mizobuchi [20] introduced another topic to BLI, apart from the 11 initial topics, to account for the sustainability of well-being. Such an addition has been also proposed by OECD as a future complement in the BLI. In contrast to Mizobuchi [19]; in Mizobuchi [20] the corrected convex non-parametric least squares (C^2NLS) method was applied for constructing the BLI. Barrington-Leigh and Escande [21] conducted a comparative study of indicators that measure progress and countries' well-being, reviewing the BLI and highlighting its advantages. In the same context, Lorenz et al. [22] developed BoD based models to estimate the weighting schemes that allow each country to attain the highest possible rank according to its BLI performance. Finally, Peiro-Palomino and Picazo-Tadeo [23] calculated the BLI based only on ten topics. They used instead the "*Life Satisfaction*" topic for comparison purposes with the calculated BLI. They employed the goal-programming model proposed by Despotis [24] for the assessment and they also performed hierarchical cluster analysis to group the assessed countries in terms of well-being. However, in these models, compensability among the different components of the indices is assumed, i.e. trade-off relations exist among the topics and a country's low performance in a topic may be "compensated" by a high performance in another topic [25].

An increasing literature body is focused on the construction of non-compensatory composite indicators. Bouyssou [26] introduced general aggregation methods that allow for a mix of compensatory and non-compensatory components. Vansnick [27] argued that the notion of relative importance of topics can only be defined in a non-compensatory framework whereas Bouyssou and Vansnick [28] provided a general study of non-compensatory preference structures. The non-compensatory aggregation methods do not allow an unfavorable value in one topic to be compensated by a favorable value in another topic [29]. Despite their desirable properties, the non-compensatory methods are not as popular as the enhanced compensatory methods, which are preferred due to their simplicity in implementation. For instance, a solution to overcome the hypothesis of compensation that retains the simplicity of the implementation is to adopt the geometric aggregation method [30]. This approach has been adopted in the case of the Human Development Index (HDI) by Chowdhury and Squire [31].

Regarding the BoD approach, non-compensability has been dealt with several ways. For the case of the Mazziotta and Pareto Index (MPI) (De Muro et al. [32]), a penalty factor is introduced for controlling the unbalanced values of some sub-indicators. The MPI is based on a data transformation based on the Z-score in order to rescale the original variables within a minimum and maximum value and potentially restrict accordingly the contribution of the sub-indicators to the total score. Vidoli and Mazziotta [33] presented the BoD-PVC approach which introduces a penalty for units that have unbalanced indicators. Fusco [34] and Vidoli et al. [35] dealt with non-compensability by utilizing directional distance functions in the BoD approach. Specifically, Fusco [34] introduced a directional penalty in the BoD model according to the variability of each topic. Firstly, Principal Component Analysis is employed to extract the importance of the topics. Then, the direction that is incorporated into the distance function and the intensity of the rates of substitution among the topics are obtained by calculating a robust kernel variance of all indicators projected onto all principal components. On the other hand, Zanella et al. [36] proposed a directional BoD model for the assessment of composite indicators and imposed weight restrictions on the virtual weights (assurance regions type I), which reflect the relative importance of the topics in percentage terms. Similarly, Rogge et al. [37] imposed weight restrictions in a directional distance BoD model.

In this paper, we take into account the discrepancy on the observed values of the indicators (level 1) over the years, by incorporating the data of previous years into a preliminary data normalization process. In

[2] The method proposed by OECD for the aggregation of the indicators of level 1 can be found in http://www.oecdbetterlifeindex.org/about/better-life-initiative/#question15.

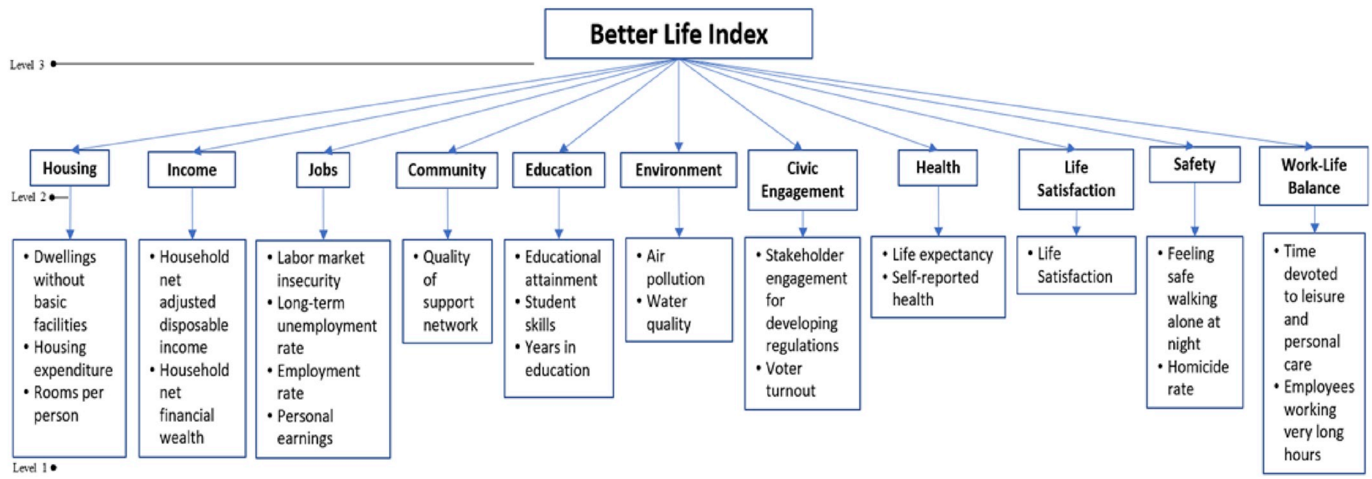

Fig. 1. The hierarchical structure of the OECD Better Life Index.

this way, we convert the absolute values of the indicators to relative ones and we smooth the deviations of indicators' values among the years. Also, we differentiate from the other studies devoted to the construction of composite indices by focusing on the whole hierarchical structure of the index and introducing a novel approach for its construction. In particular, we develop a bottom-up procedure to aggregate, in two phases, the components of the index. In the first phase of the proposed procedure, we derive through optimization the aggregation scheme of the indicators (level 1) to obtain the values of the topics that lie on the next level (level 2). Notice, that the common practice adopted in the literature employs the simple arithmetic average for the aggregation of the indicators (level 1). Then, in the second phase of the proposed procedure, we utilize the values of the 11 topics (level 2) obtained from the first phase, to derive through optimization their aggregation weighting scheme that constructs the BLI (level 3).

We model the assessment of BLI as a multiple objective programming (MOP) problem that facilitates the implementation of different concepts to derive different aggregation schemes. We convert and solve the MOP as a single objective program through scalarization. For this purpose, we employ the method of the global criterion (c.f. Mietinnen, 1999) and we formulate two different single objective models using the L_1 and the L_∞ metrics. Contrary to the BoD approach, the proposed models provide a common basis for cross-country comparisons and ranking, by implementing two different concepts. Using the L_1 metric the model carries out a "fair" and "democratic" assessment since the optimal solution is decided collectively by all countries. On the other hand, using the L_∞ metric, the model allows the weakest country to be heard and primarily decide the optimal solution.

We also incorporate in our assessments the public opinion on well-being as it is provided in the OECD web platform. To our knowledge, this is the first time that the real view of people, as recorded by an official organization, is incorporated into the assessment of a composite index, such as the BLI. Similar to Zanella et al. [36] and Rogge et al. [37] who introduced weight restrictions in their formulations to deal with the compensability, we translate the reported people's views for the eleven topics that compose the BLI into weight restrictions, to incorporate in that manner a non-compensatory preference relation in our assessments. In addition, for comparison purposes, we incorporate into the assessment two models with different properties that are based on the BoD approach, the first is the conventional BoD while the other one is the non-compensatory directional BoD (D-BoD) introduced by Fusco [34].

The rest of the paper is structured as follows. Section 2 provides the details of the OECD Better Life Index. Section 3 presents two models of the prevailing BoD approach for the construction of composite indices, the conventional BOD model as the most popular compensatory approach and the D-BoD model as the representative of the non-compensatory approach. Section 4 introduces the proposed MOP methodology with the preliminary data normalization procedure, the evaluation models and the translation of the public opinion to weight restrictions. In Section 5 the proposed approach is applied to the data of 38 OECD and partner countries for the year 2017. Comparison among different approaches and discussion are also provided. In Section 6 conclusions are drawn.

2. The OECD Better Life Index

The OECD framework covers dimensions of well-being that are universal and relevant for all people across the world. These dimensions are represented by eleven topics that compose the OECD Better Life Index. Each one of the eleven topics (level 2) of BLI is composed by one to four indicators (level 1). The indicators, as noticed in OECD [2,38]; have been chosen in accordance with theory, practice and consultation with National Statistical Offices and experts from various OECD directorates, about the issue of appropriate measuring the well-being from a comparative perspective. The hierarchical three-level structure of Better Life Index is exhibited in Fig. 1 below. The indicators lie at the first (bottom) level, the topics are at the second level and at the third level lies the resulting Better Life Index.

Among the eleven topics, the first three reflect material living conditions and the remaining eight are characterized as determinants of quality of life. A complete description of each topic and indicator included in the BLI can be found in the "How's Life?" report of OECD [2] and the web platform.[1] The OECD provides for each indicator a clear picture about the specific aspects of well-being that it covers, its unit of measurement and the source of the data. The data mostly originate from official sources such as the OECD or National Accounts, United Nations Statistics and National Statistics Offices. The latest "How's Life?" report OECD [6] includes the data of 35 OECD countries and three key partners, namely Brazil, Russia and South Africa. Shortly, other countries will be included in OECD BLI such as China, India and Indonesia. The OECD BLI web platform presents the complete profiles of the above-mentioned countries and their corresponding performance in each indicator.

As the multilateral indicators are expressed in different units (dollars, years, etc.), the composition of BLI requires a data transformation step, prior to the aggregation of the raw data. The transformation is accomplished by applying the following formula[3] to the original values

[3] The normalization formulas used by OECD for the data of the indicators of level 1 can be found in http://www.oecdbetterlifeindex.org/about/better-life-initiative/#question16.

of the indicators:

$$\frac{\text{ACV–MINOV}}{\text{MAXOV–MINOV}} \tag{1}$$

when an indicator depicts a negative aspect of well-being (e.g. air pollution) the formula is modified as:

$$1 - \frac{\text{ACV–MINOV}}{\text{MAXOV–MINOV}} \tag{2}$$

In formulas (1) and (2) ACV denotes the actual country's value, whereas MINOV and MAXOV denote the minimum and maximum observed value among all countries respectively. The normalization procedure converts the values of the indicators (level 1) in the [0,1] range, where "0" represents the worst possible performance and "1" the best possible one.

As noticed earlier, the BLI derives from the aggregation of the components that lie on three different levels. The indicators of level 1 are aggregated with equal weights to derive the values of each topic of level 2. This method,[2] besides being employed by OECD for the BLI, it also prevails in the literature. On the other hand, the OECD has not proposed any specific weighting scheme for the aggregation of the eleven topics of level 2, whereas the reported approaches in the literature are mainly devoted to this task. Up to now, OECD has focused on the dissemination of BLI and the recording of what matters most to the people about well-being. The BLI is not provided directly as an index, but the aggregation scheme of the eleven topics for its construction is left to the people. The users of the web-based application are prompted to rate the eleven topics of level 2 to build their own BLI. The preferences expressed by people are stored in a publicly accessible database that enables the cross-country comparisons and aid the OECD to better understand what is most important for the well-being. Thus, as Barrington-Leigh and Escande [21] noticed, the online platform serves also "*as a research tool because it records user interaction*". The public opinion over the significant issues of what makes for a quality life, can and should be employed by policy makers to extract valuable information for socio-economic planning.

3. Compensatory and non-compensatory BoD methods

The BoD is a prevailing approach in the literature of composite indicators and has been already utilized for the construction of the BLI [19]. The conventional form of BoD, model (3) below, can be characterized as an index maximizing linear programming model that is solved for one country at a time [39]. The composite index h_j for the specific country j ($j = 1, \ldots, n$) derives as the weighted sum $h_j = uY_j$, where $Y_j = (Y_{j1}, Y_{j2}, \ldots, Y_{jm})^T$ denotes the vector of the m components' values and $u = (u_1, u_2, \ldots, u_m)$ denotes the vector of the variables used as weights.

$$\begin{aligned} &\max h_{j_0} = uY_{j_0} \\ &s.\ t. \\ &uY_j \le 1, \quad j = 1, \ldots, n \\ &u \ge \varepsilon \end{aligned} \tag{3}$$

Model (3) is a relative measure for a composite index and is solved for one country at a time. Thus, the optimal multipliers u^* vary from country to country. The different country-specific weighting schemes derived by model (3) allow each country to achieve the highest possible score. As discussed above, the BoD model (3) is characterized by the compensability among the components of the index. However, such a compensability cannot be justified when in practical applications there is an underlying preference structure among the components of the index [34]. In that case, it is preferable to assign greatest priority to the most important component. For this purpose, Fusco [34] proposed a directional BoD (D-BoD) model by introducing a "*directional*" penalty in the BoD model. In particular, the directional distance function presented in Chambers et al. [40] is employed.

$$\begin{aligned} &\max \theta \\ &s.\ t. \\ &Y\lambda - \theta g_y \ge Y_o \\ &X\lambda + \theta g_x \le X_o \\ &\lambda \ge 0 \end{aligned} \tag{4}$$

The directional distance function model (4) is defined in terms of a production technology, where the inputs are denoted by vector X and the outputs by vector Y. Also, in model (4) the vectors g_x and g_y denote the preassigned direction in which the inputs (X) would be contracted, and the outputs (Y) would be expanded accordingly to reach the technology frontier. However, in the case of the BoD approach for the construction of composite indices, the components of inputs (X) are fixed (e.g. $X = (1, \ldots, 1)$), thus the direction of the corresponding vector is set to $g_x = 0$. In this way, model (4) becomes a directional output distance function model. Also, when the actual values of the outputs (indicators-topics) are used for the output directional vector ($g_y = Y_o$), then the D-BoD model (4) is equivalent to the BoD model (3), having assumed that $\varepsilon = 0$ in model (3) to be precise. Fusco [34] derive the directional vector g_y directly from the data, by estimating the endogenous preference structure among the components of the index using Principal Component Analysis (PCA). In particular, the direction is defined by the slope of the first principal component with the largest variance, while the other components of the directional vector g_y are obtained by the ratio of the kernel variances of the indicators-topics projected onto the principal components (for a detailed description of the methodology the reader is referred to Ref. [34]).

4. Proposed methodology

The OECD has not yet published a complete methodology for the construction of the BLI, but it continues the dialogue on the subject instead. At this point, OECD aims to prompt people to participate in the public debate about what shapes well-being and to capture their views over the eleven topics (level 2) that compose the BLI. In the proposed methodology, we take into account the public opinion about well-being by incorporating the reported views of people over the 11 topics in the assessment of BLI. Also, unlike the existing studies on BLI, we establish the connection between the indicators (level 1) across the years by employing their minimum and maximum observed values for normalization purposes. In addition, our methodology is based on a multiple objective programming assessment framework. The evaluation models are integrated in a bottom-up procedure and employed in separate phases to all levels of the composite index to derive the aggregation weighting schemes for the calculation of the values of the next level.

4.1. Normalization procedure

As reported in the OECD BLI web platform[1] the OECD normalization procedure involves, only for the year under assessment, the minimum and maximum observed values of the indicators from the participating countries. However, these values may have been changed dramatically among the years. As a result, the dispersion of the indicators' (level 1) values among the years is not considered during the necessary normalization process. This issue is also not covered by the existing approaches in the literature of BLI. On the contrary, in our approach we smooth the deviations of indicators' values and we establish cross-year compatibility by incorporating in the normalization process their minimum and maximum observed values[4] across the years (i.e. of the available data of 2013–2017). In this way, the absolute values of the indicators are converted to relative ones. We bring the above into effect

[4] The complete data of the indicators for the years 2013–2017 can be found in the online database of OECD http://stats.oecd.org/Index.aspx?DataSetCode=BLI.

by modifying the formulas (1) and (2) accordingly. For the indicators that exhibit positive contribution to the BLI (e.g. Life expectancy, Water Quality, etc.), we employ the following adjusted formula:

$$\frac{\text{ACV}-\text{MINOV}^{(2013-2017)}}{\text{MAXOV}^{(2013-2017)}-\text{MINOV}^{(2013-2017)}} \tag{5}$$

Similarly, for the indicators that exhibit negative contribution to the BLI (e.g. Housing Expenditure, Air pollution, etc.), the normalization formula becomes:

$$1-\frac{\text{ACV}-\text{MINOV}^{(2013-2017)}}{\text{MAXOV}^{(2013-2017)}-\text{MINOV}^{(2013-2017)}} \tag{6}$$

where ACV denotes the actual country's value, whereas $\text{MINOV}^{(2013-2017)}$ and $\text{MAXOV}^{(2013-2017)}$ denote the minimum and maximum observed value among all countries respectively from 2013 to 2017.

4.2. Multiple objective programming (MOP) assessment framework

In this section, we model the assessment of BLI as a multiple objective programming (MOP) problem. The BoD model (3) and the D-BoD model (4) are solved for one country at a time, thus they lack a common basis for cross-country comparisons and ranking. A common basis for fair evaluation can be established by finding a common set of multipliers u that will be used to obtain the composite index for each country. For this purpose, we formulate the following MOP model where the performance of each country ($h_j = uY_j$) is treated as a distinct objective-criterion:

$$\begin{aligned}&\max\{h_1 = uY_1, \dots, h_n = uY_n\}\\&s.\ t.\\&uY_j \le 1, \quad j = 1, \dots, n\\&u \ge \varepsilon\end{aligned} \tag{7}$$

The MOP (7) can be converted and solved as a single objective program through scalarization. For this purpose, we employ the *method of the global criterion* (c.f. Mietinnen, 1999) that is a no-preference method, i.e. no priority is assigned to the objectives. In this method, the distance between some reference point and the feasible objective region is minimized. We select the vector $e = (1, \dots, 1)$ as the reference point, because the aggregation weighting scheme should be derived under the rational assumption that yields ratings for each country as near as possible to the highest level of the index, i.e. $h_j = 1,\ j = 1, \dots, n$. The distance between the reference point and the feasible objective region can be measured by employing different metrics, thus we formulate the L_p problem as follows:

$$\begin{aligned}&\min\left(\sum_{j=1}^{n} |1 - uY_j|^p\right)^{1/p}\\&s.\ t.\\&uY_j \le 1, \quad j = 1, \dots, n\\&u \ge \varepsilon\end{aligned} \tag{8}$$

Firstly, the MOP (7) is scalarized via the method of the global criterion by employing the L_1 metric, i.e. $p = 1$ in (8), as follows:

$$\begin{aligned}&\min \sum_{j=1}^{n} (1 - uY_j)\\&s.\ t.\\&uY_j \le 1, \quad j = 1, \dots, n\\&u \ge \varepsilon\end{aligned} \tag{9}$$

The single objective model (9), also known as the *min-sum* method, simultaneously minimizes the sum of the deviations (L_1 metric) for all countries between the performance that they can achieve using the common multipliers and the selected reference point. In other words, the aim of model (9) is to maximize the performances of all countries simultaneously under a common weighting scheme. Model (9) can be straightforwardly transformed to model (10) by introducing the deviation variables ($d_j = 1 - uY_j$) at the constraints and replacing the corresponding terms in the objective function.

$$\begin{aligned}&\min \sum_{j=1}^{n} d_j\\&s.\ t.\\&uY_j + d_j = 1, \quad j = 1, \dots, n\\&u \ge \varepsilon, \quad d_j \ge 0\end{aligned} \tag{10}$$

Model (10), as it is equivalent to model (9), is solved only once and provides higher discrimination regarding the performance of the evaluated countries as well as it allows for ranking. This approach can be characterized as fair and democratic since all countries collectively and equally participate to the generation of the optimal set of weights that is commonly used to derive their performance. Notice that the optimal solution of models (9) and (10) is Pareto optimal to the MOP (7).

If the analysis is oriented to the disadvantaged countries to give them the opportunity to be heard, then the L_∞ metric can be employed, i.e. $p = \infty$ in (8). Also, the L_∞ metric can be used to examine how the countries perform by the viewpoint of the weakest one. In this way, variations on their performances can be detected. Employing the L_∞ metric, the model (7) takes the following form:

$$\begin{aligned}&\min \max_{j=1,\dots,n} [|1 - uY_j|]\\&s.\ t.\\&uY_j \le 1, \quad j = 1, \dots, n\\&u \ge \varepsilon\end{aligned} \tag{11}$$

Model (11) is also known as the *Tchebycheff* or *min-max* method that is among the most common scalarization methods in multiple criteria optimization. The canonical form of model (11) is formulated as follows:

$$\begin{aligned}&\min \delta\\&s.\ t.\\&uY_j + \delta \ge 1, \quad j = 1, \dots, n\\&uY_j \le 1, \quad j = 1, \dots, n\\&u \ge \varepsilon, \quad \delta \ge 0\end{aligned} \tag{12}$$

Notice that the optimal solution of model (12) is in general weakly Pareto optimal to the MOP (7) (c.f. [41]). Steuer and Choo [42] introduced a variant of the *Tchebycheff* method called *augmented Tchebycheff* method, which secures the Pareto optimality of the solutions. This is accomplished by adding to the objective function of model (12) the aggregate of the deviations from the reference point (L_1*-term*), which is called correction or augmentation term. We provide below the formulation of the *augmented Tchebycheff* method that we employ to derive a Pareto optimal solution to model (7):

$$\begin{aligned}&\min \delta + \rho \sum_{j=1}^{n} (1 - uY_j)\\&s.\ t.\\&uY_j + \delta \ge 1, \quad j = 1, \dots, n\\&uY_j \le 1, \quad j = 1, \dots, n\\&u \ge \varepsilon, \quad \delta \ge 0\end{aligned} \tag{13}$$

where ρ is a sufficiently small positive scalar. Model (13) minimizes the distance between the reference point and the feasible objective region by employing the augmented Tchebycheff metric. In model (13), the optimal solution is primarily determined by the largest deviation δ from the reference point, i.e. by the objective (*country*) with the lowest performance. Thus, the obtained weighting scheme (set of common weights) provides performance measures for all countries from the viewpoint of the weakest one.

4.3. Public opinion

The OECD launched the Better Life initiative and the program on Measuring Well-Being and Progress so as to find answers to questions such as "*Are our lives getting better?*", "*How can policies improve our lives?*", "*Are we measuring the right things?*", etc. As Mizobuchi [20] mentioned, "*it is particularly difficult to reach consensus on the relative importance of different socio-economic conditions*", since different weighting schemes provide different scores and country rankings that raise the argument. In the ten Step Guide published by the Competence Centre on Composite Indicators and Scoreboards of the European Commission,[5] it is noted that public opinion polls are often launched to elicit the relative weights, from a societal aspect, for the aggregation of composite indicators. In this context, the OECD BLI web platform encourages people to declare their views on the relative importance of the eleven topics of Better Life Index and records their responses. Hence, equal opportunities are given to all people worldwide to express their opinions. The OECD has not adopted an aggregation approach for BLI, as stated in the online platform: "*the OECD has not assigned rankings to countries*". Instead, the answers given online will be used to elicit valuable information about the weighting scheme that should be used in BLI.

In the context of our approach, we transfer the benefits obtained from the public deliberation by incorporating the public opinion in the assessment of BLI. Although people's authentic responses are subjective judgements, they reveal the true needs and beliefs. Hence, public opinion is the best driver for assessing the countries concerning the well-being, despite the different necessities and cultures that might exist across countries or even within same regions. Including the global responses from all parts of societies, enables us to consider equally all the different views in a democratic form of assessment. Also, the obtained results will be useful to the analyst to shape a better picture of well-being across countries, with the ultimate goal to designate and deliver accurate and successful policies.

The public responses can be incorporated into the evaluation models (3), (10) and (13) by translating them into weight restrictions [43]. We translate the public opinion to absolute limits that the weights (u) of the 11 topics (level 2) can receive (see Ref. [44]). The lower and upper bounds of the weight given to each topic derive from the minimum and maximum values of the responses for each topic. We denote the whole set of the weight restrictions with Ω.

$$u \in \Omega \tag{14}$$

Notice that by imposing rational restrictions on the weights' limits, if not eliminates, the compensation among the 11 topics of BLI assumed in the models (3), (10) and (13). Moreover, the incorporation of the weight restrictions Ω into the evaluation models does not allow the variables (weights) to get zero values at optimality. Thus, the constraints $u \geq \varepsilon$ are omitted as redundant. Alternative types of weight restrictions can be also employed, such as assurance region constraints in which upper and lower bounds are imposed on the ratio of pairs of weights [45].

5. Assessment of OECD BLI

We assess the BLI for the OECD and partner countries for the year 2017 by applying the proposed two-phase bottom-up approach.

5.1. Normalization of the raw data of indicators (level 1)

Table 1 summarizes the statistics of the indicators at level 1, as they were rescaled by means of the formulas (5) and (6). The raw data of the indicators can be found in the online database[4] of OECD.

5.2. Calculation of the topics (level 1 to level 2)

Contrary to the common practice adopted in the literature of using the simple arithmetic average for the aggregation of the indicators (level 1), we aggregate the indicators as a weighted arithmetic average, where the weights are obtained endogenously from optimization process. In order to explore alternative concepts and draw comparisons, beyond the proposed models (10) and (13) we also employ the conventional BoD model (3) and the D-BoD model (4). At the first phase of our procedure, we apply models (3), (4), (10) and (13) separately to the normalized values of the indicators (level 1) to derive the aggregation weighting scheme that yields the values of the topics (level 2). In this way, the rationale and the properties of each modelling approach are conveyed to the whole structure of the composite index. Nine out of eleven topics comprise of more than one indicator, thus we apply each model exclusively to the indicators of each topic so as to obtain its value. Notice that only two topics, namely the "Life Satisfaction" and the "Community", consist of one indicator. Therefore, the normalized values of these indicators directly become the values of the corresponding one-dimensional topics.

In Table 2, we present the resulting values of the topics that derived by utilizing the BoD model (3).

Table 3 exhibits the values of the topics that were obtained by applying the directional BoD model (4) of Fusco [34].

In Table 4, we present the values of the topics that derived by applying the min-sum model (10).

The values of the topics that derived by employing the augmented min-max model (13) are presented in Table 5.

Table 6 presents the average score of all countries in each topic as obtained from each model. Analogously, Table 7 exhibits the standard deviation of all counties' scores per topic and in each model separately. Notably, in Community (SC) and Life Satisfaction (SW) all models provide the same average score and standard deviation. This is attributed to the fact that these topics consist of a single indicator. Thus, independently of the model employed, the countries' scores on these topics coincide with the levels of the corresponding normalized indicators. Furthermore, as the BoD (3) grants the flexibility to each country to maximize its performance, it provides higher scores compared to the other models. Consequently, the average scores derived by BoD (3) are the highest ones with the lowest standard deviations in all indicators apart from Income (IW) and Education (ES), as presented in Table 7. Regarding the D-BoD (4), it is worthy to mention that, in most topics, it provides the lowest average scores but with the highest standard deviations. This is attributed to the penalizing character of the D-BoD (4) to the indicators with low variability. For instance, some countries in a few topics achieve the same scores (or close enough) with the BoD model (3), whereas the rest ones are heavily penalized. Finally, regarding the min-sum model (10) and the min-max model (13), the former yields higher average scores than the latter in all topics. This is attributed to the "*democratic*" and "*fair*" character of the min-sum model (10) where all countries together and equally decide the optimal solution. On the other hand, in min-max model (13) the country with the poorest performance plays a decisive role and primarily decides the optimal solution.

5.3. Incorporation of public opinion

To date, more than 132,566 users from 218 countries have shared their views on the OECD web platform. As noticed, the responses are updated daily, and grouped by country, age and gender. The 57% of the respondents are male while the 43% of them are female. Also, the respondents are divided into seven age groups, namely < 15, 15–24, 25–34, 35–44, 45–54, 55–64 and > 65. Most of the respondents

[5] The Competence Centre on Composite Indicators and Scoreboards is hosted in https://composite-indicators.jrc.ec.europa.eu/?q=10-step-guide.https://composite-indicators.jrc.ec.europa.eu/?q=10-step-guide.

Table 1
Descriptive statistics of the data of indicators – Level 1.

	Min	Max	Mean	Median	Variance	St.Dev.	Skew	Q1	Q3
Dwellings without basic facilities	0	1	0.907	0.984	0.032	0.179	−3.835	0.884	0.997
Housing expenditure	0.063	0.750	0.382	0.375	0.023	0.151	0.138	0.250	0.438
Rooms per person	0	0.947	0.496	0.553	0.062	0.249	−0.152	0.263	0.632
House hold net adjusted disposable income	0.061	1	0.464	0.458	0.052	0.227	0.282	0.283	0.612
House hold net financial wealth	0	1	0.271	0.214	0.050	0.223	1.158	0.094	0.397
Labour market insecurity	0.176	0.974	0.847	0.895	0.027	0.163	−2.686	0.846	0.939
Employment rate	0	1	0.575	0.605	0.036	0.191	−0.765	0.512	0.715
Long-term unemployment rate	0.129	0.999	0.836	0.899	0.037	0.191	−2.555	0.799	0.936
Personal earnings	0.107	1	0.559	0.573	0.062	0.249	−0.005	0.323	0.767
Community	0.258	0.968	0.711	0.726	0.022	0.148	−1.010	0.645	0.806
Educational attainment	0.094	1	0.722	0.789	0.062	0.250	−1.330	0.695	0.887
Student skills	0.044	0.912	0.646	0.704	0.044	0.211	−1.537	0.613	0.767
Years in education	0.099	1	0.461	0.451	0.038	0.196	0.478	0.327	0.563
Air pollution	0.500	1	0.792	0.780	0.014	0.118	−0.232	0.710	0.875
Water quality	0.182	1	0.696	0.727	0.039	0.198	−0.579	0.541	0.868
Stakeholder engagement for developing regulations	0	1	0.463	0.481	0.066	0.258	−0.019	0.259	0.667
Voter turnout	0.043	0.957	0.501	0.489	0.064	0.254	0.013	0.332	0.668
Life expectancy	0.022	1	0.839	0.899	0.030	0.173	−3.151	0.789	0.939
Self-reported health	0.050	0.967	0.624	0.667	0.054	0.233	−0.744	0.533	0.767
Life Satisfaction	0.032	0.903	0.590	0.629	0.063	0.250	−0.458	0.387	0.831
Feeling safe walking alone at night	0	0.964	0.608	0.641	0.061	0.247	−0.726	0.465	0.818
Homicide rate	0	1	0.900	0.971	0.040	0.200	−3.326	0.948	0.985
Employees working very long hours	0.269	1	0.814	0.868	0.029	0.170	−1.617	0.734	0.921
Time devoted to leisure and personal care	0.186	1	0.670	0.684	0.027	0.163	−0.924	0.593	0.742

Table 2
Data of topics derived from BoD model (3) – Level 2.

Country	HO	IW	JE	SC	ES	EQ	CG	HS	SW	PS	WL
Australia	0.972	0.699	0.942	0.839	1	0.960	1	1	0.839	0.971	0.718
Austria	0.973	0.674	0.969	0.774	0.880	0.891	0.636	0.930	0.742	0.998	0.857
Belgium	0.940	0.602	0.898	0.774	0.847	0.760	0.955	0.926	0.710	0.971	0.947
Canada	1	0.598	0.968	0.806	0.963	0.920	0.887	1	0.839	0.963	0.922
Chile	0.888	0.223	0.898	0.516	0.591	0.740	0.259	0.840	0.645	0.843	0.789
Czech Republic	0.984	0.351	0.990	0.677	1	0.782	0.679	0.828	0.613	0.978	0.881
Denmark	0.984	0.573	0.990	0.871	0.915	0.909	0.886	0.913	0.903	0.990	0.980
Estonia	0.845	0.282	0.930	0.710	0.966	0.900	0.787	0.784	0.290	0.894	0.946
Finland	0.986	0.585	0.963	0.871	1	0.940	0.674	0.941	0.903	0.966	0.922
France	0.986	0.635	0.889	0.645	0.780	0.800	0.665	0.969	0.548	0.985	1
Germany	0.997	0.706	0.988	0.774	0.929	0.891	0.638	0.904	0.742	0.993	0.913
Greece	0.986	0.235	0.480	0.452	0.681	0.700	0.502	0.926	0.161	0.971	0.846
Hungary	0.890	0.229	0.905	0.516	0.834	0.680	0.341	0.714	0.194	0.963	0.939
Iceland	1	0.615	1	0.968	0.856	1	0.727	0.979	0.903	0.989	0.678
Ireland	0.997	0.473	0.986	0.903	0.893	0.920	0.409	0.958	0.742	0.985	0.906
Israel	0.881	0.434	0.989	0.613	0.875	0.640	0.568	0.984	0.806	0.945	0.677
Italy	0.984	0.491	0.785	0.742	0.705	0.700	0.636	0.975	0.387	0.978	0.920
Japan	0.827	0.564	1	0.710	1	0.780	0.213	1	0.387	0.996	0.674
Korea	1	0.368	1	0.258	0.945	0.618	0.778	0.934	0.387	0.967	0.648
Latvia	0.651	0.186	0.839	0.581	0.959	0.840	0.615	0.666	0.387	0.766	0.958
Luxembourg	1	0.923	1	0.774	0.757	0.820	1	0.971	0.710	0.985	0.925
Mexico	0.886	0.147	0.997	0.387	0.223	0.740	1	0.699	0.613	0.354	0.362
Netherlands	1	0.568	0.987	0.710	0.886	0.891	0.795	0.946	0.871	0.991	1
New Zealand	0.995	0.443	0.971	0.871	0.862	0.960	0.810	1	0.839	0.960	0.724
Norway	1	0.765	0.991	0.839	0.865	0.960	0.705	0.976	0.903	1	0.940
Poland	0.927	0.288	0.921	0.677	0.985	0.655	0.667	0.785	0.419	0.978	0.858
Portugal	0.973	0.334	0.836	0.613	0.794	0.860	0.208	0.909	0.161	0.971	0.828
Slovak Republic	0.962	0.327	0.830	0.742	0.953	0.691	0.783	0.758	0.452	0.978	0.897
Slovenia	0.992	0.334	0.918	0.742	0.938	0.818	0.741	0.912	0.355	0.996	0.907
Spain	0.997	0.408	0.570	0.871	0.763	0.840	0.523	0.994	0.548	0.994	0.968
Sweden	1	0.618	0.948	0.774	0.909	0.940	0.886	0.978	0.839	0.971	0.981
Switzerland	1	0.783	1	0.839	0.922	0.945	0.667	1	0.903	0.998	0.857
Turkey	0.824	0.236	0.886	0.581	0.535	0.660	0.864	0.806	0.258	0.945	0.269
United Kingdom	0.989	0.557	0.976	0.806	0.816	0.840	0.864	0.919	0.645	1	0.752
United States	1	1	1	0.710	0.951	0.860	0.950	1	0.710	0.834	0.756
Brazil	0.819	0.099	0.889	0.710	0.316	0.860	0.733	0.708	0.613	0.023	0.848
Russia	0.690	0.225	0.946	0.710	1	0.760	0.409	0.543	0.419	0.595	1
South Africa	0.750	0.085	0.201	0.645	0.211	0.620	0.591	0.638	0.032	0.642	0.671

HO: Housing, IW: Income, JE: Jobs, SC: Community, ES: Education, EQ: Environment, CG: Civic engagement, HS: Health, SW: Life Satisfaction, PS: Safety, WL: Work-Life Balance.

Table 3
Data of topics derived from D-BoD model (4) – Level 2.

Country	HO	IW	JE	SC	ES	EQ	CG	HS	SW	PS	WL
Australia	0.777	0.189	0.541	0.839	1	0.706	1	1	0.839	0.391	0.202
Austria	0.783	0.172	0.733	0.774	0.399	0.333	0.145	0.526	0.742	0.907	0.373
Belgium	0.606	0.131	0.464	0.774	0.220	0.241	0.671	0.512	0.710	0.391	0.519
Canada	1	0.130	0.612	0.806	0.706	0.535	0.438	1	0.839	0.397	0.543
Chile	0.250	0.028	0.266	0.516	0.111	0.222	0.034	0.303	0.645	0.094	0.268
Czech Republic	0.858	0.051	0.910	0.677	1	0.180	0.174	0.286	0.613	0.463	0.422
Denmark	0.858	0.118	0.880	0.871	0.420	0.423	0.431	0.467	0.903	0.713	0.729
Estonia	0.304	0.038	0.528	0.710	0.536	0.474	0.269	0.231	0.290	0.153	0.633
Finland	0.880	0.123	0.717	0.871	1	0.610	0.170	0.571	0.903	0.494	0.536
France	0.880	0.148	0.440	0.645	0.228	0.286	0.164	0.723	0.548	0.566	1
Germany	0.974	0.193	0.883	0.774	0.535	0.333	0.148	0.440	0.742	0.725	0.496
Greece	0.880	0.030	0.084	0.452	0.161	0.189	0.091	0.509	0.161	0.391	0.352
Hungary	0.432	0.029	0.452	0.516	0.320	0.175	0.048	0.172	0.194	0.338	0.604
Iceland	1	0.138	1	0.968	0.306	1	0.206	0.793	0.903	0.879	0.173
Ireland	0.974	0.082	0.877	0.903	0.333	0.535	0.063	0.663	0.742	0.588	0.487
Israel	0.426	0.071	0.858	0.613	0.412	0.151	0.113	0.841	0.806	0.262	0.173
Italy	0.858	0.088	0.266	0.742	0.080	0.189	0.145	0.764	0.387	0.463	0.531
Japan	0.323	0.115	1	0.710	1	0.262	0.026	1	0.387	0.841	0.102
Korea	1	0.055	1	0.258	0.518	0.091	0.258	0.537	0.387	0.363	0.109
Latvia	0.157	0.022	0.322	0.581	0.679	0.344	0.137	0.142	0.387	0.084	0.695
Luxembourg	1	0.544	1	0.774	0.232	0.313	1	0.733	0.710	0.566	0.547
Mexico	0.439	0.017	0.801	0.387	0.010	0.222	1	0.166	0.613	0.023	0.054
Netherlands	1	0.116	0.881	0.710	0.266	0.333	0.274	0.591	0.871	0.734	1
New Zealand	0.949	0.074	0.499	0.871	0.243	0.706	0.297	1	0.839	0.316	0.174
Norway	1	0.245	0.894	0.839	0.361	0.706	0.188	0.776	0.903	1	0.605
Poland	0.560	0.039	0.497	0.677	0.852	0.140	0.167	0.233	0.419	0.463	0.377
Portugal	0.783	0.048	0.338	0.613	0.115	0.381	0.025	0.452	0.161	0.394	0.322
Slovak Republic	0.718	0.046	0.327	0.742	0.670	0.151	0.264	0.207	0.452	0.463	0.460
Slovenia	0.924	0.048	0.528	0.742	0.575	0.222	0.222	0.462	0.355	0.859	0.492
Spain	0.974	0.064	0.085	0.871	0.098	0.344	0.096	0.934	0.548	0.798	0.615
Sweden	1	0.139	0.407	0.774	0.463	0.610	0.431	0.788	0.839	0.438	0.839
Switzerland	1	0.265	1	0.839	0.516	0.515	0.167	1	0.903	0.942	0.370
Turkey	0.319	0.030	0.142	0.581	0.019	0.163	0.381	0.257	0.258	0.250	0.035
United Kingdom	0.901	0.112	0.749	0.806	0.287	0.344	0.387	0.486	0.645	1	0.212
United States	1	1	1	0.710	0.642	0.381	0.655	1	0.710	0.218	0.235
Brazil	0.311	0.011	0.444	0.710	0.038	0.381	0.213	0.182	0.613	0.002	0.358
Russia	0.147	0.028	0.575	0.710	1	0.241	0.063	0.090	0.419	0.043	1
South Africa	0.122	0.006	0.022	0.645	0.023	0.140	0.123	0.150	0.032	0.034	0.130

HO: Housing, IW: Income, JE: Jobs, SC: Community, ES: Education, EQ: Environment, CG: Civic engagement, HS: Health, SW: Life Satisfaction, PS: Safety, WL: Work-Life Balance.

belong to the groups 15–24 (33%) and 25–34 (28%). The complete list of the responses of people worldwide is publicly available at the web platform.[6] In this study, we have chosen to include the 117,434 responses that derive from the citizens of the 35 members of the OECD and the 3 partner countries for which OECD provides data and metrics. Table 8 presents the normalized weights for the 11 topics (level 2), which are retrieved from the responses of the 38 countries that participate in the assessment. The last row of Table 8 contains the representative (total) weights of the worldwide responses as provided by OECD.

Fig. 2 depicts the variability of the weights[7] presented in Table 8. As shown for example, responses originated from Australia (numbered 1 in Table 8) give the highest priority to Work-Life Balance (WL), which is characterized as extreme outlier. As can be seen, the topic Civic Engagement (CG) has been assigned the lowest weight values.

As noticed in Section 4.3, the public opinion can be incorporated into the evaluation models by translating it into direct weight restrictions. In Table 9 we present the lower and upper bounds that the weight of each topic can receive. These bounds derive from the minimum and maximum values of each column (topic) of Table 8. The whole set of the weight restrictions is denoted with Ω (14).

5.4. Calculation of the BLI (level 2 to level 3)

At the second phase of our bottom-up procedure we employ, similar to the first phase, the models (3), (4), (10) and (13) to derive the BLI for each country under each different concept and draw comparisons. However, at this phase we incorporate into the models (3), (10) and (13) the weight restrictions Ω described in Table 9. Also, we employ the D-BoD model (4) without the weight restrictions Ω because this model is mainly used as an alternative to the additional constraints, derived from the public opinion, which treat the compensation in the assessment.

In Table 10, we present the results obtained by applying each of the aforementioned approaches to the corresponding data of the topics that derived in the first phase of the bottom-up procedure (see Section 5.2). In particular, we apply the BoD model (3), with the weight restrictions Ω, to the data of Table 2. The BLI scores as well as the ranking are presented in column 5 of Table 10. Also, we apply the D-BoD model (4) to the data of Table 3 and we present the corresponding results at the column 3 of Table 10. Similarly, the column 6, present the BLI scores and the ranking derived by applying the min-sum model (10), with the weight restrictions Ω, to the data of Table 4. The column 7 of Table 10 exhibit the BLI scores and the ranking that obtained by applying the min-max model (13), with the weight restrictions, Ω to the data of Table 5. For comparison purposes, we also present in column 4 of Table 10 the results obtained by applying the BoD model (3), without the weight restrictions Ω, to the data of Table 2. In addition, the second column of Table 10, exhibits the ranking of the countries obtained

[6] The complete data of the responses can be found in the OECD web platform http://www.oecdbetterlifeindex.org/bli/rest/indexes/stats/country.

[7] o denotes outlier, * denotes extreme outlier.

Table 4
Data of topics derived from min-sum model (10) – Level 2.

Country	HO	IW	JE	SC	ES	EQ	CG	HS	SW	PS	WL
Australia	0.970	0.699	0.942	0.839	0.916	0.960	1	0.985	0.839	0.971	0.718
Austria	0.973	0.674	0.965	0.774	0.880	0.740	0.412	0.930	0.742	0.993	0.857
Belgium	0.938	0.602	0.883	0.774	0.767	0.760	0.824	0.926	0.710	0.971	0.917
Canada	0.995	0.598	0.959	0.806	0.963	0.920	0.887	0.951	0.839	0.956	0.921
Chile	0.746	0.223	0.840	0.516	0.586	0.740	0.240	0.840	0.645	0.843	0.789
Czech Republic	0.984	0.351	0.980	0.677	1	0.660	0.679	0.828	0.613	0.978	0.881
Denmark	0.984	0.573	0.986	0.871	0.892	0.880	0.765	0.913	0.903	0.982	0.962
Estonia	0.814	0.282	0.924	0.710	0.911	0.900	0.787	0.784	0.290	0.894	0.946
Finland	0.986	0.585	0.955	0.871	1	0.940	0.674	0.941	0.903	0.956	0.922
France	0.986	0.635	0.870	0.645	0.765	0.800	0.665	0.969	0.548	0.985	0.847
Germany	0.997	0.706	0.984	0.774	0.929	0.780	0.638	0.904	0.742	0.993	0.909
Greece	0.986	0.235	0.368	0.452	0.680	0.700	0.502	0.926	0.161	0.971	0.846
Hungary	0.884	0.229	0.901	0.516	0.834	0.680	0.262	0.714	0.194	0.963	0.939
Iceland	1	0.615	1	0.968	0.833	1	0.543	0.979	0.903	0.974	0.678
Ireland	0.997	0.473	0.929	0.903	0.853	0.920	0.163	0.946	0.742	0.985	0.906
Israel	0.881	0.434	0.988	0.613	0.870	0.640	0.258	0.970	0.806	0.945	0.677
Italy	0.984	0.491	0.755	0.742	0.500	0.700	0.475	0.975	0.387	0.978	0.920
Japan	0.827	0.564	1	0.710	1	0.780	0.213	1	0.387	0.996	0.538
Korea	0.886	0.368	1	0.258	0.923	0.500	0.778	0.932	0.387	0.967	0.558
Latvia	0.651	0.186	0.835	0.581	0.957	0.840	0.615	0.666	0.387	0.766	0.952
Luxembourg	1	0.923	0.960	0.774	0.740	0.820	0.620	0.971	0.710	0.985	0.925
Mexico	0.886	0.147	0.945	0.387	0.112	0.740	1	0.696	0.613	0.354	0.361
Netherlands	1	0.568	0.968	0.710	0.810	0.780	0.475	0.946	0.871	0.985	1
New Zealand	0.992	0.443	0.936	0.871	0.786	0.960	0.810	0.958	0.839	0.960	0.683
Norway	1	0.765	0.991	0.839	0.865	0.960	0.629	0.976	0.903	0.985	0.940
Poland	0.927	0.288	0.919	0.677	0.985	0.620	0.643	0.785	0.419	0.978	0.858
Portugal	0.973	0.334	0.798	0.613	0.334	0.860	0.208	0.909	0.161	0.971	0.828
Slovak Republic	0.962	0.327	0.806	0.742	0.943	0.640	0.783	0.758	0.452	0.978	0.897
Slovenia	0.992	0.334	0.890	0.742	0.938	0.740	0.679	0.912	0.355	0.985	0.907
Spain	0.997	0.408	0.509	0.871	0.512	0.840	0.462	0.994	0.548	0.985	0.913
Sweden	1	0.618	0.912	0.774	0.906	0.940	0.733	0.974	0.839	0.971	0.981
Switzerland	1	0.783	0.988	0.839	0.922	0.760	0.588	1	0.903	0.989	0.857
Turkey	0.824	0.236	0.728	0.581	0.223	0.660	0.756	0.806	0.258	0.945	0.269
United Kingdom	0.989	0.557	0.976	0.806	0.816	0.840	0.864	0.919	0.645	1	0.733
United States	0.997	1	0.969	0.710	0.951	0.860	0.950	0.851	0.710	0.828	0.756
Brazil[a]	0.819	0.099	0.879	0.710	0.308	0.860	0.733	0.688	0.613	0.000	0.848
Russia	0.627	0.225	0.941	0.710	0.998	0.760	0.163	0.543	0.419	0.595	1
South Africa[b]	0.000	0.061	0.191	0.645	0.205	0.620	0.489	0.049	0.032	0.642	0.604

HO: Housing, IW: Income, JE: Jobs, SC: Community, ES: Education, EQ: Environment, CG: Civic engagement, HS: Health, SW: Life Satisfaction, PS: Safety, WL: Work-Life Balance.

[a] The performance of Brazil in topic *Safety (PS)* is very low, in fact it attains 0.0000002.

[b] The performance of South Africa in topic *Housing (HO)* is very low, in fact it attains 0.00001.

directly from the OECD platform given the same importance to the 11 topics. Notice that the online platform does not provide the BLI scores of the countries but only their ranking.

The conventional BoD model (3) without the weight restrictions Ω and the D-BoD of Fusco [34] rank many countries in the first position, thus the comparisons with the ranking provided from the OECD web platform cannot be safely drawn. On the contrary, as we observe from Table 10, the rankings derived by models (3), (10) and (13) with the weight restrictions Ω are close to the ranking provided from the OECD web platform. In these four rankings Norway is ranked first while South Africa is ranked last. Comparing the rankings obtained from model (13) with the Ω and the OECD web platform, we observe slight differences, e.g. Australia 7/3, Austria 14/17 and Israel 21/24. The major differences between the ranking of model (3) with the Ω and the ranking of the OECD web platform, are detected for Luxembourg 7/14, Belgium 16/12 and Iceland 11/7. The major differences between the ranking of model (10) with the Ω and the ranking of the OECD web platform, are detected for Finland 2/9, Spain 25/19, Luxembourg 9/14, Portugal 33/28 and Slovak Republic 21/26.

We observe from the results presented in Table 10 that Norway is ranked first by all models and attains the highest performance. On the other hand, South Africa is ranked at the last position by all models except from the D-BoD model of Fusco [34] that deems Chile as the country with the lowest performance. As expected, the conventional BoD model (3) yields the highest possible score for each country (the average score is 0.984) and lacks discriminating power since 25 countries out of the 38 are deemed as BLI efficient. The D-BoD model deems 22 out of 38 countries as BLI efficient and the average score is 0.858. On the contrary, the inclusion of public opinion with the form of weight restrictions Ω in the BoD model (3), imposes limits to the trade-offs among the 11 topics of BLI and reduces drastically the compensation among them. Indeed, the BoD model (3) with the weight restrictions Ω identifies only one country as BLI efficient, namely Norway, and the obtained average score is considerably lower than the one derived from the BoD model (3). There is a reduction of 12,1% (from 0.984 to 0.865) between the average scores obtained from the BoD model (3) and the BoD model (3) with the weight restrictions Ω.

Comparing the D-BoD model of Fusco [34] with the BoD model (3) with Ω, we observe that the former yields lower scores in average (0.858 vs 0.865), although it deems many countries as BLI efficient (22 out of 38). This is attributed to the special character of the D-BoD model that rewards and penalizes some countries based on the variance of the data. To be clearer, the scores derived by the D-BoD model have high variance. Indeed, the rest inefficient countries have remarkably lower scores in average than the corresponding ones derived from the BoD model (3) with Ω. Thus, the large number of efficient countries is counterbalanced by the low scores of the inefficient countries. Although the D-BoD model generates scores with high variation, it cannot discriminate adequately between the efficient and the inefficient countries. On the other hand, the incorporation of the weight restrictions Ω

Table 5
Data of topics derived from min-max model (13) – Level 2.

Country	HO	IW	JE	SC	ES	EQ	CG	HS	SW	PS	WL
Australia	0.787	0.546	0.942	0.839	1	0.928	1	0.984	0.839	0.549	0.718
Austria	0.719	0.536	0.925	0.774	0.731	0.796	0.446	0.815	0.742	0.869	0.857
Belgium	0.719	0.595	0.828	0.774	0.781	0.748	0.844	0.861	0.710	0.681	0.917
Canada	0.694	0.551	0.966	0.806	0.812	0.896	0.824	0.997	0.839	0.872	0.921
Chile	0.796	0.178	0.882	0.516	0.524	0.634	0.210	0.649	0.645	0.310	0.789
Czech Republic	0.560	0.261	0.929	0.677	0.781	0.705	0.616	0.681	0.613	0.637	0.881
Denmark	0.571	0.507	0.954	0.871	0.912	0.891	0.783	0.826	0.903	0.912	0.962
Estonia	0.816	0.203	0.898	0.710	0.745	0.823	0.725	0.565	0.290	0.613	0.946
Finland	0.625	0.409	0.906	0.871	1	0.929	0.647	0.820	0.903	0.909	0.922
France	0.729	0.512	0.809	0.645	0.667	0.760	0.661	0.814	0.548	0.661	0.847
Germany	0.786	0.550	0.939	0.774	0.855	0.821	0.627	0.755	0.742	0.779	0.909
Greece	0.556	0.177	0.198	0.452	0.569	0.609	0.484	0.851	0.161	0.515	0.846
Hungary	0.835	0.186	0.881	0.516	0.644	0.644	0.275	0.581	0.194	0.307	0.939
Iceland	0.570	0.512	1	0.968	0.813	1	0.571	0.895	0.903	0.987	0.678
Ireland	0.740	0.379	0.813	0.903	0.854	0.835	0.201	0.937	0.742	0.772	0.906
Israel	0.728	0.397	0.981	0.613	0.606	0.558	0.306	0.967	0.806	0.671	0.677
Italy	0.613	0.437	0.683	0.742	0.545	0.623	0.500	0.798	0.387	0.450	0.920
Japan	0.616	0.558	0.957	0.710	0.822	0.774	0.201	0.513	0.387	0.680	0.538
Korea	1	0.293	1	0.258	0.828	0.544	0.763	0.462	0.387	0.554	0.558
Latvia	0.478	0.145	0.814	0.581	0.791	0.751	0.562	0.463	0.387	0.487	0.952
Luxembourg	0.792	0.718	0.931	0.774	0.548	0.792	0.679	0.834	0.710	0.706	0.925
Mexico	0.672	0.093	0.978	0.387	0.155	0.621	0.902	0.668	0.613	0.196	0.361
Netherlands	0.790	0.543	0.905	0.710	0.836	0.821	0.525	0.879	0.871	0.878	1
New Zealand	0.478	0.382	0.960	0.871	0.773	0.914	0.790	1	0.839	0.571	0.683
Norway	0.953	0.500	0.984	0.839	0.812	0.955	0.641	0.913	0.903	1	0.940
Poland	0.584	0.202	0.897	0.677	0.830	0.633	0.571	0.633	0.419	0.599	0.858
Portugal	0.721	0.268	0.716	0.613	0.557	0.831	0.208	0.576	0.161	0.708	0.828
Slovak Republic	0.545	0.216	0.743	0.742	0.615	0.659	0.708	0.697	0.452	0.483	0.897
Slovenia	0.884	0.241	0.814	0.742	0.849	0.769	0.592	0.759	0.355	0.944	0.907
Spain	0.682	0.321	0.519	0.871	0.648	0.724	0.471	0.864	0.548	0.914	0.913
Sweden	0.787	0.574	0.938	0.774	0.869	0.935	0.757	0.931	0.839	0.779	0.981
Switzerland	0.736	0.760	0.936	0.839	0.802	0.829	0.504	0.943	0.903	0.931	0.857
Turkey	0.701	0.147	0.842	0.581	0.390	0.544	0.772	0.719	0.258	0.491	0.269
United Kingdom	0.575	0.521	0.949	0.806	0.712	0.805	0.808	0.810	0.645	0.808	0.733
United States	0.906	1	0.979	0.710	0.746	0.811	0.877	0.950	0.710	0.740	0.756
Brazil	0.695	0.071	0.837	0.710	0.234	0.730	0.732	0.702	0.613	0.022	0.848
Russia	0.677	0.135	0.921	0.710	0.715	0.546	0.201	0.377	0.419	0.322	1
South Africa	0.478	0.071	0.198	0.645	0.155	0.559	0.504	0.377	0.032	0.022	0.604

HO: Housing, IW: Income, JE: Jobs, SC: Community, ES: Education, EQ: Environment, CG: Civic engagement, HS: Health, SW: Life Satisfaction, PS: Safety, WL: Work-Life Balance.

Table 6
Average score for each topic as derived by each approach.

Model	HO	IW	JE	SC	ES	EQ	CG	HS	SW	PS	WL
BoD model (3)	0.936	0.465	0.902	0.711	0.824	0.818	0.686	0.887	0.590	0.903	0.833
D-BoD model (4)	0.720	0.126	0.606	0.711	0.431	0.357	0.281	0.552	0.590	0.475	0.441
Min-sum model (10)	0.907	0.464	0.878	0.711	0.774	0.792	0.604	0.864	0.590	0.900	0.817
Min-max model (13)	0.700	0.387	0.851	0.711	0.698	0.756	0.592	0.760	0.590	0.640	0.817

Table 7
Standard Deviation of scores for each topic as derived by each approach.

Model	HO	IW	JE	SC	ES	EQ	CG	HS	SW	PS	WL
BoD model (3)	0.091	0.226	0.161	0.148	0.204	0.110	0.214	0.121	0.250	0.198	0.163
D-BoD model (4)	0.300	0.175	0.299	0.148	0.309	0.203	0.263	0.298	0.250	0.293	0.260
Min-sum model (10)	0.179	0.227	0.173	0.148	0.247	0.118	0.236	0.175	0.250	0.200	0.169
Min-max model (13)	0.129	0.214	0.185	0.148	0.202	0.129	0.218	0.175	0.250	0.252	0.169

improves the discriminating power of the BoD model (3). Similarly, we deduce from the results of models (10) and (13) that the weight restrictions Ω play a key role in the assessment. We provide in Table 11 the average score, the standard deviation of the scores and the number of the BLI efficient countries derived by each model.

The optimal solution of the min-sum model (10) is decided collectively by all countries, i.e. all countries are assessed under a common weighting scheme. Thus, the min-sum model (10) generates lower scores than the BoD approach and has higher discriminating power. Indeed, the min-sum model (10) with Ω deems as BLI efficient only one country (namely Norway) and in average yields lower scores in comparison with the BoD model (3) with Ω and the D-BoD model (4). In general, the BLI scores derived from the min-sum model (10) with Ω are lower than the scores of BoD model (3) with Ω, the average reduction of the BLI scores is 2.82%, with a significant reduction of 30.5% to the performance of South Africa (0.358 vs 0.515). However, for three

Table 8
Normalized weights retrieved from OECD about the topics of level 2.

	Country	HO	IW	JE	SC	ES	EQ	CG	HS	SW	PS	WL
1	Australia	0.090	0.087	0.084	0.074	0.098	0.083	0.063	0.103	0.099	0.092	0.127
2	Austria	0.091	0.083	0.086	0.080	0.098	0.095	0.068	0.107	0.103	0.097	0.091
3	Belgium	0.094	0.087	0.087	0.079	0.100	0.092	0.065	0.107	0.103	0.092	0.094
4	Canada	0.090	0.088	0.089	0.080	0.099	0.091	0.064	0.107	0.104	0.096	0.093
5	Chile	0.090	0.089	0.092	0.076	0.106	0.092	0.073	0.104	0.096	0.090	0.093
6	Czech Republic	0.085	0.092	0.092	0.076	0.098	0.094	0.068	0.104	0.103	0.098	0.090
7	Denmark	0.083	0.081	0.087	0.081	0.103	0.094	0.073	0.102	0.112	0.091	0.094
8	Estonia	0.096	0.090	0.090	0.078	0.099	0.097	0.067	0.103	0.100	0.099	0.083
9	Finland	0.087	0.083	0.085	0.079	0.099	0.098	0.069	0.105	0.107	0.097	0.091
10	France	0.094	0.087	0.091	0.088	0.099	0.092	0.062	0.108	0.099	0.088	0.093
11	Germany	0.090	0.084	0.086	0.083	0.099	0.092	0.068	0.105	0.109	0.090	0.094
12	Greece	0.086	0.090	0.092	0.077	0.102	0.092	0.066	0.110	0.100	0.094	0.090
13	Hungary	0.092	0.090	0.085	0.084	0.096	0.093	0.062	0.101	0.105	0.099	0.095
14	Iceland	0.097	0.089	0.090	0.081	0.101	0.085	0.064	0.108	0.094	0.104	0.087
15	Ireland	0.088	0.089	0.089	0.083	0.099	0.087	0.068	0.101	0.111	0.085	0.100
16	Israel	0.094	0.103	0.088	0.077	0.103	0.082	0.064	0.107	0.101	0.088	0.093
17	Italy	0.086	0.082	0.093	0.083	0.098	0.095	0.072	0.104	0.103	0.088	0.095
18	Japan	0.090	0.088	0.087	0.081	0.098	0.087	0.063	0.103	0.102	0.111	0.090
19	Korea	0.093	0.089	0.088	0.080	0.096	0.086	0.069	0.097	0.107	0.101	0.094
20	Latvia	0.087	0.094	0.087	0.080	0.094	0.097	0.069	0.093	0.103	0.097	0.097
21	Luxembourg	0.089	0.098	0.094	0.078	0.092	0.093	0.062	0.106	0.101	0.093	0.092
22	Mexico	0.091	0.091	0.092	0.076	0.104	0.088	0.074	0.100	0.097	0.093	0.092
23	Netherlands	0.093	0.085	0.084	0.079	0.099	0.092	0.067	0.105	0.111	0.092	0.095
24	New Zealand	0.088	0.085	0.086	0.081	0.099	0.096	0.067	0.102	0.108	0.091	0.097
25	Norway	0.093	0.088	0.090	0.079	0.095	0.092	0.065	0.107	0.105	0.093	0.095
26	Poland	0.090	0.094	0.091	0.078	0.101	0.086	0.061	0.098	0.109	0.098	0.095
27	Portugal	0.088	0.084	0.093	0.078	0.096	0.090	0.069	0.104	0.104	0.099	0.096
28	Slovak Republic	0.085	0.088	0.092	0.081	0.096	0.093	0.068	0.104	0.104	0.097	0.091
29	Slovenia	0.089	0.084	0.087	0.083	0.099	0.102	0.065	0.101	0.099	0.100	0.092
30	Spain	0.086	0.084	0.091	0.078	0.102	0.087	0.075	0.109	0.097	0.094	0.097
31	Sweden	0.088	0.084	0.089	0.079	0.097	0.096	0.070	0.105	0.107	0.090	0.095
32	Switzerland	0.090	0.089	0.089	0.083	0.097	0.092	0.064	0.103	0.106	0.092	0.093
33	Turkey	0.091	0.093	0.088	0.083	0.099	0.090	0.073	0.100	0.095	0.094	0.094
34	United Kingdom	0.091	0.089	0.090	0.079	0.098	0.091	0.062	0.105	0.111	0.086	0.097
35	United States	0.086	0.087	0.087	0.081	0.099	0.092	0.063	0.104	0.112	0.091	0.098
36	Brazil	0.090	0.087	0.089	0.074	0.107	0.087	0.065	0.104	0.102	0.103	0.092
37	Russia	0.096	0.095	0.090	0.080	0.094	0.088	0.074	0.100	0.095	0.096	0.092
38	South Africa	0.095	0.093	0.091	0.074	0.096	0.088	0.061	0.100	0.106	0.097	0.100
	Total	0.090	0.088	0.089	0.080	0.099	0.090	0.066	0.104	0.104	0.092	0.097

HO: Housing, IW: Income, JE: Jobs, SC: Community, ES: Education, EQ: Environment, CG: Civic engagement, HS: Health, SW: Life Satisfaction, PS: Safety, WL: Work-Life Balance.

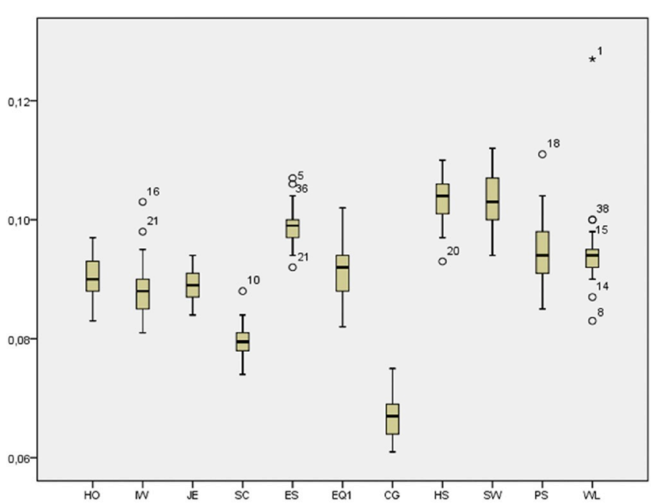

Fig. 2. Boxplots of the weights of the 11 topics derived by the public opinion.

countries the BLI scores of the former are higher, namely for Finland (0.99 (2) vs 0.985 (8)), Latvia (0.764 (28) vs 0.762 (30)) and United Kingdom (0.918 (14) vs 0.915 (17)). This clearly occurs because in our bottom-up procedure we separately apply each model to all levels of the BLI. As a result, in the 2nd phase of the bottom-up procedure each model is applied to different data (values of topics). Notice that the values of the topics (level 2) are derived in the 1st phase of the bottom-up procedure, by applying separately each model to the values of the indicators (level 1). Thus, the resulting values of the topics (level 2) obtained from the different approaches are generally different (data of Tables 2–5).

The BLI scores derived from the min-max model (13) with Ω, are in average considerably lower than the ones obtained from the other approaches, for instance we observe an average reduction of 11.03% and 8.86% in comparison with the BoD model (3) with Ω and the min-sum model (10) with Ω respectively. The scores obtained from the min-max model (13) with Ω are remarkably decreased for all countries as compared with the corresponding ones derived by the BoD model (3) with Ω. For instance, there is a significant reduction on the performance of Greece by 21% (0.565 vs 0.716) and Slovak Republic by 18% (0.69 vs 0.846). Also, the scores obtained from the min-max model (13) with Ω are decreased for all countries but one, namely South Africa (0.364 vs 0.358), as compared with the corresponding ones obtained from the min-sum model (10) with Ω. Again, we spot significant reduction on the performance of some countries, for instance the performance of Greece is decreased by 20% (0.565 vs 0.705) and the one of Italy by 18% (0.69 vs 0.807).

The discrepancies on the BLI scores derived by models (10) and (13), with the weight restrictions Ω, are clearly justified by the different optimality criterion of each model. Although each model yields a common optimal solution for all the countries, these solutions are generally different. The optimal solution of model (10) with Ω is

Table 9
Lower and Upper bounds of the weights of the eleven topics – Level 2.

	HO	IW	JE	SC	ES	EQ	CG	HS	SW	PS	WL
Lower Bound	0.083	0.081	0.084	0.074	0.092	0.082	0.061	0.093	0.094	0.085	0.083
Upper Bound	0.097	0.103	0.094	0.088	0.107	0.102	0.075	0.110	0.112	0.111	0.127

HO: Housing, IW: Income, JE: Jobs, SC: Community, ES: Education, EQ: Environment, CG: Civic engagement, HS: Health, SW: Life Satisfaction, PS: Safety, WL: Work-Life Balance.

Table 10
BLI scores – Level 3.

Country	OECD ranking with equal importance	D-BoD (4) Ranking		BoD model (3) Ranking		BoD model (3) with Ω Ranking		min-sum model (10) with Ω Ranking		min-max model (13) with Ω Ranking	
Australia	(3)	1	(1)	1	(1)	0.992	(4)	0.984	(5)	0.925	(7)
Austria	(17)	0.783	(27)	0.998	(26)	0.940	(14)	0.912	(16)	0.850	(14)
Belgium	(12)	0.812	(26)	1	(1)	0.935	(15)	0.917	(15)	0.865	(12)
Canada	(5)	1	(1)	1	(1)	0.991	(5)	0.990	(2)	0.942	(3)
Chile	(31)	0.332	(38)	0.898	(37)	0.747	(31)	0.729	(31)	0.638	(31)
Czech Republic	(21)	1	(1)	1	(1)	0.889	(19)	0.880	(19)	0.755	(22)
Denmark	(2)	1	(1)	1	(1)	0.997	(3)	0.986	(4)	0.935	(5)
Estonia	(22)	0.653	(31)	1	(1)	0.844	(24)	0.837	(22)	0.747	(23)
Finland	(9)	1	(1)	1	(1)	0.985	(8)	0.990	(2)	0.923	(8)
France	(18)	1	(1)	1	(1)	0.904	(18)	0.883	(18)	0.786	(19)
Germany	(13)	0.977	(23)	1	(1)	0.956	(12)	0.949	(11)	0.879	(11)
Greece	(35)	0.880	(24)	0.986	(30)	0.716	(34)	0.705	(34)	0.565	(35)
Hungary	(32)	0.432	(36)	0.968	(34)	0.745	(33)	0.738	(30)	0.622	(34)
Iceland	(7)	1	(1)	1	(1)	0.974	(11)	0.960	(8)	0.913	(9)
Ireland	(15)	1	(1)	1	(1)	0.935	(15)	0.910	(17)	0.844	(15)
Israel	(24)	0.768	(29)	0.989	(29)	0.853	(22)	0.832	(23)	0.759	(21)
Italy	(25)	0.858	(25)	0.985	(31)	0.843	(25)	0.807	(27)	0.690	(26)
Japan	(23)	1	(1)	1	(1)	0.837	(26)	0.816	(26)	0.694	(25)
Korea	(29)	1	(1)	1	(1)	0.800	(28)	0.764	(28)	0.671	(28)
Latvia	(30)	0.501	(34)	0.984	(32)	0.762	(30)	0.764	(28)	0.661	(29)
Luxembourg	(14)	1	(1)	1	(1)	0.986	(7)	0.952	(9)	0.863	(13)
Mexico	(37)	1	(1)	1	(1)	0.628	(37)	0.613	(37)	0.558	(37)
Netherlands	(10)	1	(1)	1	(1)	0.975	(9)	0.935	(12)	0.910	(10)
New Zealand	(11)	1	(1)	1	(1)	0.947	(13)	0.931	(13)	0.841	(16)
Norway	(1)	1	(1)	1	(1)	1	(1)	1	(1)	0.973	(1)
Poland	(27)	0.631	(32)	0.996	(27)	0.828	(27)	0.826	(24)	0.709	(24)
Portugal	(28)	0.783	(27)	0.973	(33)	0.775	(29)	0.720	(33)	0.643	(30)
Slovak Republic	(26)	0.743	(30)	0.993	(28)	0.846	(23)	0.841	(21)	0.690	(26)
Slovenia	(20)	1	(1)	1	(1)	0.877	(20)	0.863	(20)	0.808	(18)
Spain	(19)	1	(1)	1	(1)	0.865	(21)	0.825	(25)	0.776	(20)
Sweden	(4)	1	(1)	1	(1)	0.990	(6)	0.981	(6)	0.943	(2)
Switzerland	(6)	1	(1)	1	(1)	0.998	(2)	0.976	(7)	0.936	(4)
Turkey	(36)	0.411	(37)	0.950	(35)	0.677	(35)	0.623	(36)	0.565	(35)
United Kingdom	(16)	1	(1)	1	(1)	0.915	(17)	0.918	(14)	0.831	(17)
United States	(8)	1	(1)	1	(1)	0.975	(9)	0.952	(9)	0.935	(5)
Brazil	(34)	0.569	(33)	0.909	(36)	0.668	(36)	0.660	(35)	0.626	(32)
Russia	(33)	1	(1)	1	(1)	0.747	(31)	0.725	(32)	0.626	(32)
South Africa	(38)	0.454	(35)	0.752	(38)	0.515	(38)	0.358	(38)	0.364	(38)

Table 11
No of BLI efficient countries, average score and standard deviation derived by each model.

	BoD model (3)	BoD model (3) with Ω	D-BoD model (4)	Min sum model (10) with Ω	Min max model (13) with Ω
No of BLI efficient countries	25	1	22	1	0
Average score	0.984	0.865	0.858	0.843	0.770
Standard deviation of scores	0.045	0.121	0.209	0.137	0.143

absolutely determined by all countries, since all the constraints, except the ones imposed by the weight restrictions, should structurally be binding at optimality. On the other hand, the optimal solution of the min-max model (13) with Ω is determined by the country whose performance has the largest deviation from the selected reference point (ideal rating), i.e. the binding constraint corresponds to South Africa. Clearly, South Africa plays a key role in model (13), although we did not assign any priority to this country. This holds because it is a structural property of model (13) to give the opportunity to the weakest country to be heard and let the optimal solution to be primarily decided by the country with the poorest performance. Thus, the obtained weighting scheme provides performance measures for all countries by the viewpoint of the weakest one. This justifies also the reduction in the performance in all other countries than South Africa. Obviously, this effect is mitigated to some extent by bringing into play the views of people about well-being, i.e. the weight restrictions Ω. This happens because the voice of the rest countries can be still heard in model (13) via the weight restrictions Ω. Indeed, the BLI scores and ranking derived by model (13) with Ω indicate that Norway is still ranked first even though the weighting scheme is primarily decided by the weakest

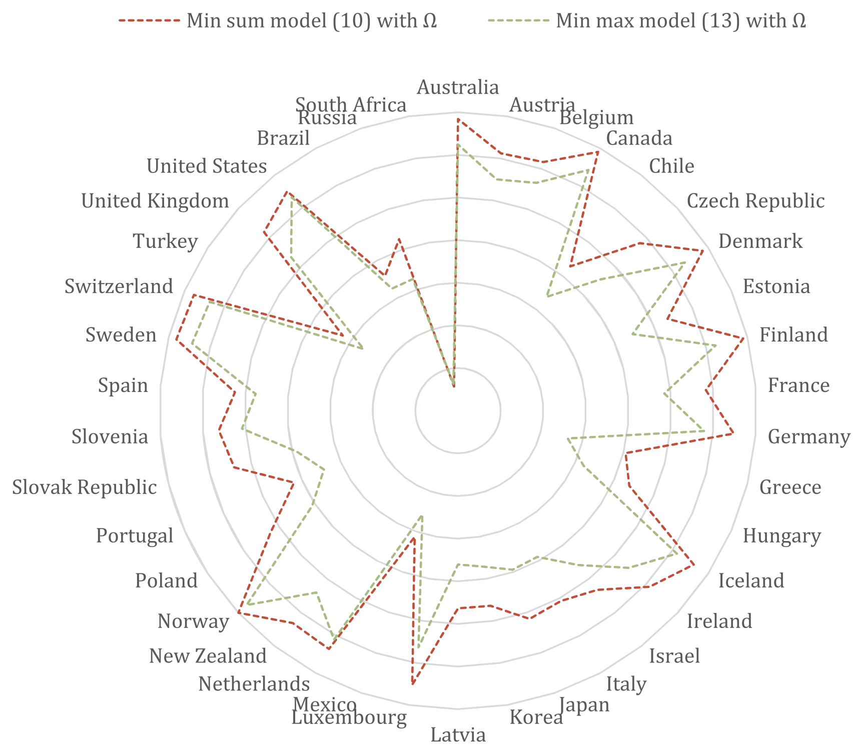

Fig. 3. BLI scores as derived by models (10) and (13) with Ω

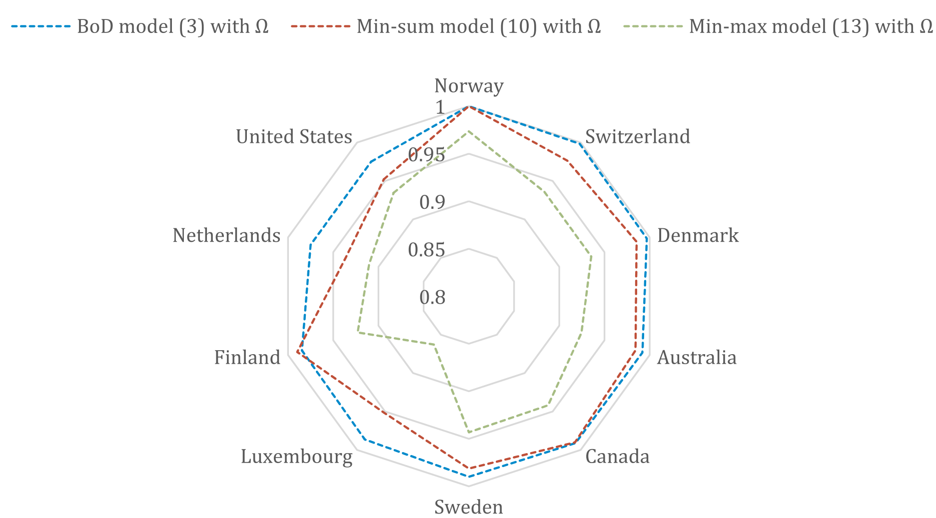

Fig. 4. Top 10 countries.

country (South Africa) that is ranked at the last position. The South Africa clearly does not act like a benchmark for Norway, since model (13) with Ω does not deem any country as BLI efficient. This is attributed to the impact of the weight restrictions Ω. Notice that when the weight restrictions are omitted from model (13), at optimality, only Australia and Norway are deemed as BLI efficient, which are also the *benchmarks* of South Africa in this case.

A general observation is that the BLI scores obtained from all models as well as the rankings differentiate. However, for the most countries we do not observe great differences on the rankings generated by models (10) and (13), with the weight restrictions Ω. Considerable differentiations are observed for Finland (2/8), Luxembourg (9/13) and Switzerland (7/4). Thus, we conclude that the incorporation of the public opinion, in the form of the weight restrictions Ω, restrain significantly the flexibility of the models and play a crucial role to the assessment of BLI. Notice that these models without the weight restrictions yield very different scores and rankings. In Fig. 3 we provide a schematic representation of the BLI scores derived by the models (10) and (13), of our approach, with the weight restrictions Ω.

The results reveal that there is a clear divide between the Nordic countries as well as Switzerland, Australia and Canada which achieve high BLI scores and the rest countries that generally achieve relatively low BLI scores. The results verify the objective reality of the balanced economic growth with the well-being in the aforementioned countries. In Fig. 4 we present the countries ranked in Top 10 by models (3), (10) and (13) with the weight restrictions Ω. It is noteworthy that the top five rankings provided by the above mentioned models include only eight countries. Notice that the Southern and Eastern European

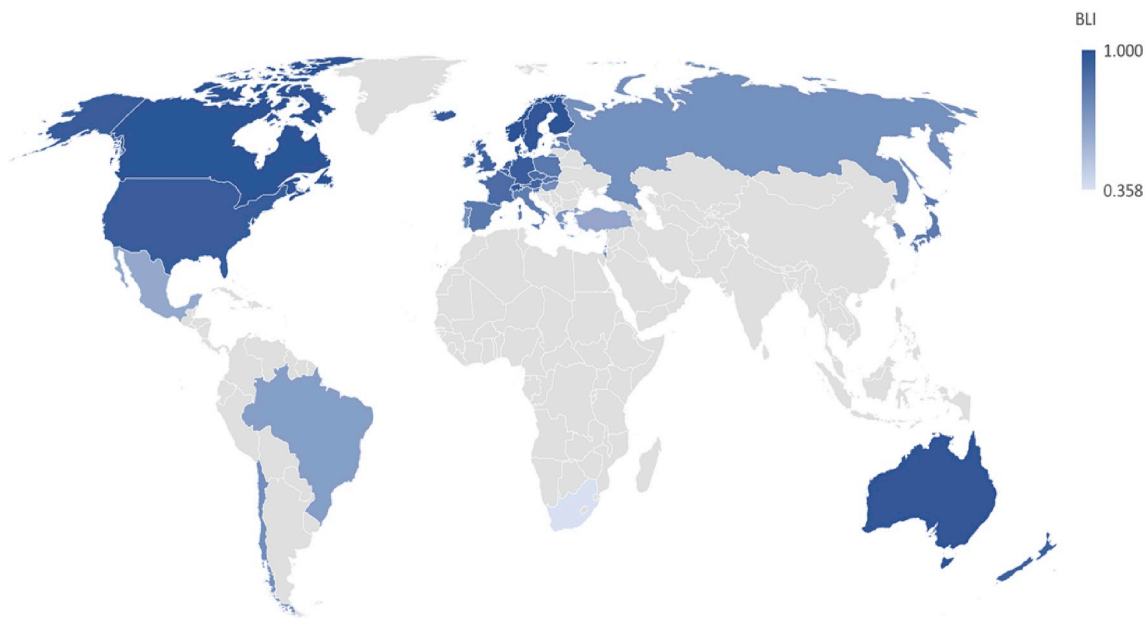

Fig. 5. Heat map of the BLI performance of the 38 countries provided by the min-sum model (10) with Ω

countries are absent from the Top 10 as well as the countries from Asia, South America and Africa.

Based on the analysis of the results and the characteristics of the min-sum model (10) with Ω and the min-max model (13) with Ω, we propose the former for the evaluation of BLI as it is more democratic than the latter one. It also establishes a common basis for fair evaluation assessment, where the weighting scheme is determined jointly by all the countries and none of them is favored. In addition, the min-sum model (10) with Ω proves to have higher discriminating power than the other models used for comparison purposes, i.e. the BoD model (3) and the D-BoD model (4). As more revealing than mere numbers is the full picture of the 38 countries under evaluation, we provide in Fig. 5 a visualization of their performance as derived by the min-sum model (10) with Ω. In the heat map of Fig. 5 the darker colors indicate high performance while the brighter colors indicate low performance.

6. Conclusion

In this paper we introduced a novel methodology for the assessment of the OECD BLI, which can be also applied readily for the assessment of other composite indices. Our methodology absorbs possible extreme variations of indicators' values between the years, as it incorporates data from previous years into the normalization process. We proposed a hierarchical bottom-up procedure for the aggregation of the components of BLI that lie on different levels. We obtain the values of each topic (level 2) from optimization process, instead of commonly aggregating with equal weights the indicators (level 1) that they comprise. As we noted, this aggregation method is adopted so far in the literature, for the calculation of the topics. We formulated the assessment of BLI as a multiple objective programming (MOP) problem where the performance of each country is treated as a distinct objective-criterion. We proposed two scalarizing methods for the MOP that secure the Pareto optimality of the results, but they have different properties and thus they provide different BLI scores. In addition, for comparison purposes we employed the conventional BoD approach and the non-compensatory directional BoD approach of Fusco [34]. Also, we incorporated into the assessment the public opinion that is captured from the global responses in the web platform of OECD BLI. We specify a non-compensatory preference relation for the weights of the topics by translating the reported views of people into weight restrictions. These weight restrictions are incorporated, at the 2nd phase of the bottom-up procedure, into the evaluation models to reduce the compensation effect. In this way, based on rational bounds that originate directly from the public opinion, we reduce the effect of compensation that might be imposed by the adopted modelling approach.

We applied our approach to the data of 38 countries (35 OECD and 3 Non-OECD economies) for the year 2017. Each modelling approach was applied to all levels of BLI to examine how the performance of each country is affected under the different concepts. Our findings illustrate that the public opinion in the form of weight restrictions can effectively drive the optimization process and depict the collective preferences to the BLI scores. Also, the results verify the real living conditions of the assessed countries. From the presented models, we propose the use of the min-sum model (10), because it establishes a "*fair*" and "*democratic*" assessment, where the aggregation weighting scheme of the components of the index is decided collectively and equally by all countries. Also, this model with the weight restrictions has greater discriminating power than the directional BoD model (4).

Given the global concern and priority for the countries to improve the quality of life for their citizens, our approach can be utilized for aiding the design of policies via well-being measurement or as a policy assessment framework. It would be interesting though, in the evaluation of BLI, to take into account external factors that affect the components of BLI, such as the spatial heterogeneity of the evaluated countries [46]. This addition would balance the regional differences of the countries and thus, would provide useful insights for the policy makers.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seps.2019.03.005.

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