Sensitivity of environmental performance index based on stochastic dominance

Mehmet Pinar*

Abstract

The Environmental Performance Index (EPI) is a popular sustainability index. It is a composite index which ranks 180 countries based on their environmental performance in 32 indicators. Using the EPI data and stochastic dominance efficiency methodology, this paper examines the sensitivity to the subjective weights assigned to the indicators and categories of environmental performance. The findings show a remarkable variation in environmental performance based on alternative weights which are selected using Stochastic Dominance criteria. Except for 2020, the environmental health category in EPI gets relatively higher importance in the optimal scenario, and ecosystem vitality gets relatively higher weights in the inferior scenario, suggesting that the environmental health category achievements have been relatively higher for most countries over time. The ranking analysis also shows major variations in country rankings with alternative weights. Two countries, Maldives and Gabon, would have experienced more than 100 position changes in their rankings with alternative weights. Furthermore, 67 countries would have experienced 30 or more position changes in their rankings and 37 countries experienced an EPI score change of more than 50 (out of 100) with alternative weights. Overall, the results illustrate the importance of sensitivity analysis of composite indices to increase reliability and transparency.

Keywords: composite index; environmental performance; indicators; stochastic dominance

This is the author-accepted manuscript for the article: Pinar, M. (2022). Sensitivity of environmental performance index based on stochastic dominance. Journal of Environmental Management, 310, 114767. https://doi.org/10.1016/j.jenvman.2022.114767

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*Business School, Edge Hill University, Ormskirk, Lancashire, L39 4QP, UK, Email: mehmet.pinar@edgehill.ac.uk

1. Introduction

The adverse effects of climate change have been well-documented such as the loss of productivity in agriculture, decreased grain yields, coastal flooding, loss of biodiversity, forest and crop fires, water shortages, increased risk of illness, among many others (see e.g., Dell et al., 2014; Dellink et al., 2019; IPCC, 2014; Michetti and Pinar, 2019; Parry et al., 2007). Thus, the consequences of climate change have become one of the most pressing concerns of the world. Therefore, to capture and measure the environmental conditions of countries, there has been increasing use of composite indices.

One of the most known sustainability composite indices is the Environment Performance Index (EPI) of the Yale Center for Environmental Law and Policy, Yale University, which considers 32 indicators to assess the environmental performance in 180 countries (Wendling et al., 2020). In addition, other environmental performance indices were constructed with the use of different indicators and aggregation methods (see e.g., Agyemang et al., 2021; Cao and Bian, 2021; Caravaggio et al., 2019; García-Alvarez and Moreno, 2018; García-Sánchez et al., 2015; Iqbal et al., 2021; Zuo et al., 2017). These environmental indices are also widely used as an environmental quality proxy to examine environmental quality's relationship with other concepts (e.g., Adeel-Farooq et al., 2021; Ahmad and Amin, 2020; das Neves Almeida et al., 2017; Elsalih et al., 2020; Hao et al., 2018; Mavragani et al., 2016).

Even though these composite indices provide a more holistic environmental performance of countries and are widely used by the empirical literature as a proxy for environmental quality, these composite indices rely on various normative choices such as the choice of environmental performance indicators, normalization of these indicators before the aggregation, the importance given to indicators, and so on (see e.g., OECD, 2008 for the detailed stages followed to construct composite indices). It has been well-documented that these normative choices in the construction of indices lead to uncertainty and sensitivity of these composite indices, for general review (e.g., Saisana et al., 2005; Greco et al., 2019), for the review on the composite environmental indicators (Burgass et al., 2017), for the sensitivity of composite EPI scores (Papadimitriou et al., 2020). Even though Papadimitriou et al. (2020) examined the sensitivity of composite EPI scores when weights allocated to environmental health and ecosystem vitality allowed to vary +/- 25% of the benchmark weights, the construction of the EPI involves many benchmark weights (see section 2 for the details of how EPI is constructed). This paper will use stochastic dominance (SD) concepts to investigate the sensitivity of EPI scores based on alternative weight choices.

SD concepts have been widely used in the decision-making literature in uncertain conditions. The concept was first introduced by Atkinson (1970) and has been used to compare poverty and wellbeing distributions (e.g., Atkinson, 1987; Barrett and Donald, 2003, Davidson and Duclos, 2000, Duclos et al., 2005; Ferre et al., 2012; Foster and Shorrocks, 1988; Van de gaer et al., 2014). These SD comparisons were motivated by the poverty and wellbeing distributions and based on the concept of the veil of ignorance (Anderson and Post, 2018; Liang, 2017).

Recently, SD efficiency (SDE) methods were introduced to allow a complete diversification by examining whether a given portfolio is efficient or whether there are alternative ways of combining assets that dominate the benchmark market (Post, 2003; Kuosmanen, 2004; Roman et al., 2006; Post and Versijp, 2007; Scaillet and Topaloglou, 2010; Linton et al., 2014; Arvanitis and Topaloglou, 2017; Fang and Post, 2017; Post and Poti, 2017). However, the SDE methodology has also become a popular methodology to test for the sensitivity of composite indices over the last years (see e.g., Agliardi et al., 2012, 2014; 2015; Bernardo et al., 2021; Mehdi, 2019; Pinar et al., 2013; Pinar, 2015; Pinar et al., 2015; Pinar et al., 2017; Pinar et al., 2019; Pinar et al., 2020).

SD methodology could be applied to random variables such as the outcome of medical treatments (Leshno and Levy, 2004), the agricultural yields (Bekele, 2005; Nolan and Santos, 2019) and financial investment return (Post and Kopa, 2017; Sharma and Mehra, 2017). However, SD methodology can also be applied as a partial order for comparing non-stochastic variables in the face of ambiguity about the relevant multi-criteria objective function. For example, in wellbeing analysis, the social planner has preferences over the cross-sectional distribution of wealth or income. This cross-sectional distribution is deterministic and is determined by policy measures like redistribution policies. The seminal study by Atkinson (1970) proves the equivalence between second-degree stochastic dominance and a dual inequality ordering. Some other studies also used SD methodology to compare other wellbeing distributions (Barrett and Donald, 2003; Duclos and Échevin, 2011; Anderson and Post, 2018), Therefore, SD methodology could also be used as a partial order for non-stochastic prospects in the face of ambiguity about preferences in multi-criteria decision making. For instance, Pinar et al. (2020) used SD methodology to obtain feasible multidimensional poverty outcomes when weights assigned to indicators are allowed to vary (i.e., ambiguity based on alternative weight choices). The application in this paper is also closely associated with the multidimensional criteria where there is ambiguity about preferences of weights allocated to the environmental performance criteria and assesses the sensitivity (ambiguity) of the environmental performances.

The current SD application is closely associated with the works of Anderson and Post (2018) and Anderson et al. (2020). Anderson and Post (2018) develop SD optimality and inferiority concepts to identify wellbeing distributions with the highest and lowest levels of shared prosperity, respectively. On the other hand, Anderson et al. (2020) provide utopia and dystopia indices which consist of the 'greatest elements' (universally dominating scenario) and 'least elements' (university dominated solution) of the choice sets, respectively.

However, neither of these papers examine the greatest and least elements when the weights allocated to different wellbeing indicators are allowed to vary. Henceforth, in the similar spirit to Anderson and Post (2018) and Anderson et al. (2020), and by using the SD super-efficiency tests proposed by Scaillet and Topaloglou (2010), this paper aims to test whether the cross-country distribution of sustainability scores ‘majorizes’ the distribution of every alternative weighting scheme and whether it itself is not majorized by an alternative (see Arvanitis et al. (2021) for the generalization of the SD super-efficiency tests). There is no theoretical underpinning to argue that one indicator used in constructing EPI is more important than another one, and therefore, the sensitivity of the cross-country distribution of sustainability scores is analyzed when the normative weights allocated to indicators are allowed to vary.

The remainder of the paper is organized as follows. Section 2 compares the proposed methodology with the existing other methods. Section 3 gives the details of how the EPI is constructed. Section 4 briefly offers the SDE methodology, and the results are provided in Section 4. Finally, section 5 concludes.

2. Comparison of the proposed methodology with alternative methodologies

The data envelopment analysis (DEA) is another popular method that has been used to test for the sensitivity of the composite scores (see e.g., Zhou et al., 2007; Cherchye et al., 2007, 2008; Rogge, 2012; Tofallis, 2013; Athanassoglou, 2015, 2016; Van Puyenbroeck and Rogge, 2017). For instance, Caravaggio et al. (2019) employ the DEA method to obtain an air quality index for the European countries. Even though DEA methods are used to construct the most optimistic and pessimistic scenarios (or best and worst scenarios) with the use of alternative weight choices, the weights chosen for each country maximize or minimize the composite indicator relative to the other countries and the weights allocated to indicators vary across countries. For instance, Rogge (2012) uses a DEA model as proposed by Zhou et al. (2007) and shows that each country allocates a full weight to indicator in which their environmental performance is highest. The allocation of different weights to different indicators for each country leads to undesirable and incomparable outcomes as each country's performance is obtained by allocating full weight to an indicator in which this country performs the best or worst. Compared to DEA methods, the proposed methodology obtains the 'greatest' and 'least' elements of choice set using the same weight sets for all the countries involved.

Another method that is commonly used to avoid the subjective (normative) choice of weights is the principal component analysis (PCA), which aims to reduce the original set of indicators to a smaller set with the linear combinations (see e.g., Khatum, 2009; Singh et al., 2012; Abou-Ali and Abdelfattah, 2013; Smits and Steendijk, 2015; das Neves Almeida, 2017; Shaker, 2018, for the use of PCA to obtain composite indices). However, even though PCA deals with the potential collinearity among indicators and avoids double-counting, the PCA methodology does not offer any sensitivity of composite indices based on the alternative weight allocation across indicators (see e.g., Mazziotta and Pareto, 2019 for the detailed review of the use and misuse of PCA). However, the proposed method in this paper obtains weight sets that would majorize cross-country distribution of sustainability scores and would not be majorized by an alternative, allowing us to offer the sensitivity of environmental performance.

3. Measurement of Environmental Performance Index

Like the other composite indices, the construction of EPI goes through various stages (see OECD, 2008 for the detailed steps). In their technical appendix, Wendling et al. (2020) provide the details of the stages followed to build EPI. Firstly, the EPI includes 32 environmental performance indicators clustered under two policy objectives: i) environmental health and ii) ecosystem vitality. Each policy objective includes different issue categories and indicators. Table 1 lists the policy objectives, issue categories, indicators, and respective weights assigned to categories and indicators to obtain composite EPI scores.

<Insert Table 1 approximately here>

The broad category of environmental health includes four issue categories: i) air quality; ii) sanitation and drinking water; iii) heavy metals; and iv) waste management. The environmental health includes seven indicators: i) particulate matter (PM) with a diameter of 2.5 μm or less ($PM_{2.5}$); ii) household solid fuels; iii) Ozone exposure; iv) unsafe sanitation; v) unsafe drinking water; vi) lead exposure; and vii) solid waste management. All these indicators, except waste management, measure the number of age-standardized disability-adjusted life-years lost per 100,000 persons due to $PM_{2.5}$ exposure, use of solid household fuels, ground-level ozone pollution, inadequate sanitation facilities, unsafe drinking water, lead contamination in the environment, respectively. Finally, solid waste management measures the proportion of household and commercial waste generated in a country that is collected and treated.

The broad category of ecosystem vitality has seven issue categories: i) biodiversity and habitat; ii) ecosystem services; iii) fisheries; iv) climate change; v) pollution emissions; vi) agriculture; and vii) water resources. The biodiversity and habitat category consists of seven indicators: i) terrestrial biome protection (TBP) with the use of national weights, which is based on the protection levels based on the presence of biome type within that country (TBP – national); ii) TBP with the use of global weights, which is based on the protection levels based on the presence of biome type globally (TBP – global); iii) marine protected areas; iv) protected areas representativeness index (PARI); v) species habitat index (SHI); vi) species protection index (SPI); and vii) biodiversity habitat index (BHI). The category of ecosystem services includes three indicators: i) tree cover loss (TCL); ii) grassland loss (GL); and iii) wetland loss (WL). The category of fisheries also covers three indicators: i) fish stock; ii) marine trophic index (MTI); and iii) fish caught by trawling (FCT). The climate change category includes different types of emissions that are closely associated with climate change, including: i) carbon dioxide (CO_2) growth rate (CO_2-GR); ii) methane (CH_4) growth rate (CH_4-GR); iii) fluorinated gas (F gas) growth rate (F-gas-GR); iv) Nitrous oxide (N_2O) growth rate (N_2O-GR); v) black carbon growth rate (BC-GR); vi) CO_2 emissions growth from land cover (CO_2-GR-LC); vii) greenhouse gas (GHG) emissions growth rate (GHG-GR); and viii) GHG emissions per capita (GHG-PC). On the other hand, two different types of emissions are put into the pollutions emissions category: i) Sulfur dioxide (SO_2) growth rate (SO_2-GR); and ii) Nitrogen Oxide (NO_x) growth rate (NO_x-GR). Finally, agriculture and water resources categories include one indicator: Sustainable Nitrogen Management Index (SNMI) and the percentage of wastewater treatment, respectively.

All these indicators are normalized and standardized to range between 0 and 100, where higher scores represent better environmental performance.The EPI is obtained using the benchmark weights for environmental health and ecosystem vitality policy categories: 40% and 60%, respectively. On the other hand, each issue category/indicator is allocated respective weights given in Table 1. The overall contribution of each indicator to the final overall score is calculated and shown in the last column of Table 1. The CO2 growth rate and PM2.5 exposure contributions are relatively higher compared to other indicators with 13.2% and 11% weights, respectively. In comparison, the contributions of the grassland and wetland losses to the overall index are minor, with weights of 0.3%. Finally, the remaining indicators contribute to the overall index with weights ranging between 1 and 2%. The details of the indicator measurement, the sources of the data, and each indicator's normalization procedure are provided in the technical appendix of Wendling et al. (2020).

Table 2 provides the descriptive statistics of each indicator, category and overall index. Overall achievement levels in different indicators, categories, and policy categories show a good level of variation. For example, average achievement scores in the fisheries category are the lowest, suggesting that countries' overall performance concerning fisheries is weak. On the other hand, on average, countries perform better in the pollution emissions category. Concerning the indicators, countries perform the best in reducing F-gas growth rates. Similarly, countries’ performances in some indicators under the biodiversity and habitat category (i.e., TBP – global, TBP – national, SPI and SHI) are also relatively strong. Overall, there is a good variation in countries’ environmental performance across indicators and categories. Therefore, the weighted average calculation of the EPI scores allows compensation of the lower achievements in some categories with relatively higher achievements in other categories. In that respect, alternative weight allocation across different indicators and categories could lead to volatility in environmental performance.

<Insert Table 2 approximately here>

4. Methodology

A $d \times N$ matrix consists of $\boldsymbol{E}$ environmental indicators that take values in $\mathbb{R}^d$. These observations consist of the realization of achievements in d environmental indicators of N countries. Let $F(\boldsymbol{y})$ is the continuous cumulative distribution function (cdf) of $E = (E_1, E_2, \dots, E_d)'$ at point $e = (e_1, e_2, \dots, e_d)'$. The benchmark weights used in constructing environmental composite scores are defined as a vector of $\mathbf{w}$ (i.e., weights provided in Table 1). An alternative weighting vector of $\boldsymbol{w}_a \in \mathbb{L}$ is considered where $\mathbb{L} \coloneqq (\boldsymbol{w}_a \in \mathbb{R}^m_+ : \mathbf{e}'\boldsymbol{w}_a = 1)$ with $\mathbf{e}$ being a vector of ones suggesting that all indicators have non-negative weights and weights sum to one. $G(s, \boldsymbol{w}; F)$ and $G(s, \boldsymbol{w}_a; F)$ are cdfs of the composite scores of $\boldsymbol{w}'\boldsymbol{E}$ and $\boldsymbol{w}_a'\boldsymbol{E}$ at point s, which are obtained as follows, respectively: $G(s, \boldsymbol{w}; F) = \int_{\mathbb{R}^d} \mathbb{I}\{\boldsymbol{w}'\boldsymbol{u} \leq s\} dF(\boldsymbol{u})$ and $G(s, \boldsymbol{w}_a; F) = \int_{\mathbb{R}^d} \mathbb{I}\{\boldsymbol{w}_a'\boldsymbol{u} \leq s\} dF(\boldsymbol{u})$. s represents an environmental performance score ranging between 0 and 100. $\mathbb{I}$ is an indicator function, and $\boldsymbol{u}$ is an increasing monotonic function of such that $\boldsymbol{u}'(s) > 0$.

Whether the cross-country distribution of sustainability scores 'majorizes' the distribution of every alternative weighting scheme is tested as follows:

$G(s, \boldsymbol{w}; F) > G(s, \boldsymbol{w}_a; F)$ for some $s \in \mathbb{R}$ and for some $\boldsymbol{w}_a \in \mathbb{L}$.

The weighted Kolmogorov-Smirnov type test statistic is used as follows:

$$\hat{S} \coloneqq \frac{\sqrt{N}}{N} \sup_{s, \boldsymbol{w}_a} \left[G\left(s, \boldsymbol{w}; \hat{F}\right) - G\left(s, \boldsymbol{w}_a; \hat{F}\right)\right]$$

where $G\left(s, \boldsymbol{w}; \hat{F}\right)$ and $G\left(s, \boldsymbol{w}_a; \hat{F}\right)$ are the empirical counterparts of the respective cross-country distribution of sustainability scores with benchmark and alternative weights. In the opposite scenario, to obtain the weights that offer the least elements, the order of the cumulative distribution functions is changed. Finally, to obtain the test statistic, a subsampling bootstrap method is used, which is adopted by Linton et al. (2005). The Gurobi Solver of the General Algebraic Modelling System (GAMS) software package is used to solve the optimization problem (see Scaillet and Topaloglou (2010) for the details of the SDE methodology; Pinar et al. (2017) for cross-country application).

5. Results

The bottom-up approach is used to construct EPI scores. In other words, indicators are used to obtain 11 category composite indices, and then category composite indices are used to obtain environmental health and ecosystem vitality, and EPI scores.Therefore, the sensitivity of the category composite indices located under the environmental health and ecosystem vitality policy objective categories is tested in the first application. Table 3 offers the indicator weights that would majorize cross-country distributions of sustainability scores and is not majorized by an alternative, respectively. These scenarios are called optimal and inferior scenarios for the sake of simplicity.[1] In each category, at least one indicator contributes to the optimal and inferior scenario with relatively more weights. For instance, the F-gas growth rate contributes relatively more to the climate change category in the optimal scenario. On the other hand, GHG per capita and CO_2 growth rate indicators are the main contributors to the inferior scenario in the climate change category. This finding suggests that cross-country performances are relatively better in terms of F-gas growth rate, and relatively worse in terms of GHG emissions and CO_2 growth rates. On the other hand, if the unsafe sanitation (unsafe drinking water) indicator was used as a sole indicator for the Sanitation & Drinking Water category, then the cross-country performance in this category would have been better (worse). Similarly, the same trend occurs in different categories where some indicators get more weight in the optimal and inferior scenarios, suggesting if these indicators had been allocated more importance, then the cross-country distributions of the performances would have dominated (dominated) by the benchmark performance distributions. In other words, the environmental performance of countries would have been much better (worse) when indicators in optimal and inferior scenarios get more weight.

<Insert Table 3 approximately here>

Figure 1 provides cumulative climate change composite index outcomes with the benchmark, optimal and inferior scenarios to show the sensitivity of the category composite scores with alternative weighting schemes more explicitly. This figure provides the number of countries (x-axis) that surpass a composite score (y-axis) with different scenarios. For instance, 91, 6 and 112 countries among 113 countries have a composite score below 70 with

[1] Note that a balanced data set is needed to carry out the SDE methodology. Therefore, the number of observations used in each category varies based on the availability of the data for indicators.

the benchmark, optimal and inferior scenarios, respectively. This data clearly shows that there is a remarkable variation in climate change composite scores with alternative weighting schemes. In other words, if the performances of countries in the climate change category were only based on the GHG per capita and CO_2 growth rates, with respective weights in Table 3 inferior scenario, then only one country would have a score above 70 compared to 22 countries in the benchmark scenario. Clearly, the choice of indicators and weights given to these indicators dramatically alter the performance of countries in the climate change category.

<Insert Figure 1 approximately here>

The optimal and inferior scenarios for the policy categories (environmental health and ecosystem vitality) and EPI are also obtained when categories under the environmental health, ecosystem vitality and EPI are allocated different weights. Table 4 offers the results. The lead exposure category contributes the most to the optimal scenario for the environmental health policy category. In contrast, air quality and waste management categories contribute 47.7% and 52.3% to the inferior scenario, respectively. In other words, if the environmental health had been constructed based on performances in these two categories with roughly equal weights, then the distribution of the environmental health performances would have been dominated by any alternative index. On the other hand, pollution emissions, biodiversity and habitat, and climate change categories contribute to the ecosystem vitality optimal scenario with weights of 52.5%, 34.5% and 13%, respectively. In comparison, the fisheries category is the main contributor to the ecosystem vitality inferior scenario. Finally, out of 11 categories, only four categories contribute to the optimal scenario EPI where pollution emissions, biodiversity and habitat, climate change and lead exposure contribute with weights of 42.6%, 27.8%, 16.6% and 13%, respectively. On the other hand, with 70.5% weight, the fisheries category is the main category contributing to the inferior scenario EPI. The findings suggest that the choice of only some categories to construct EPI would have resulted in a distribution of achievements that would dominate and are dominated by the benchmark performance index.

<Insert Table 4 approximately here>

Figure 2 presents the cumulative distributions of the EPI composite index with the benchmark, optimal and inferior scenarios. There are higher (lower) numbers of countries with a score above a given composite score with the optimal (inferior) case scenario compared to benchmark one at all composite scores. For instance, 112, 82 and 5 countries have a composite score above 40 with the optimal, benchmark and inferior scenarios, respectively. Furthermore, the composite achievements of countries also show major variation. For instance, 37 countries experienced an EPI score change of more than 50 (out of 100) with alternative weights. Since some categories were allocated no weight in both inferior and optimal scenarios, it is clear that exclusion of these categories while obtaining composite EPI scores would have led to higher variability in composite scores.

<Insert Figure 2 approximately here>

The country rankings with the benchmark, optimal and inferior scenarios highlight major rank reversals among 132 countries when alternative weights are used to obtain EPI scores.[2] Figure 3 provides the number of countries with an absolute rank difference between three scenarios (i.e., benchmark, optimal and inferior scenarios). Overall, there is a significant rank variation among countries when different weights are used to construct EPI scores. The rank difference between the three scenarios is at least 30 positions for 67 countries. The rank difference for the two countries amongst the three scenarios is even more than 100 positions.

[2] To preserve space, ranking analysis only considers EPI scores obtained with the benchmark, optimal and inferior scenarios, however, country rankings with other policy categories and issue categories are available from author upon request.

For instance, Maldives is ranked in 6th position with the inferior scenario compared to the 132nd position with the optimal scenario. On the other hand, Gabon is ranked 25th with the optimal scenario compared to the 128th position in the inferior scenario (see Appendix Table A1 for the EPI scores and rankings with the benchmark, optimal and inferior scenarios). Overall, the ranking analysis suggests that the choice of categories (indicators) and the importance of these categories (indicators) could lead to significant rank variations in the composite scores.

<Insert Figure 3 approximately here>

6. Robustness analysis

Some of the baseline optimal and inferior scenarios resulted in corner solutions as some of the indicators and categories were excluded while constructing these two scenario indices (i.e., some indicators and categories were allocated zero weights). To avoid the exclusion of indicators and categories from the construction of optimal and inferior indices, lower bounds of weights are imposed. In other words, some reasonable lower bound weight is used, which has been also used by the existing literature (see e.g., Foster et al., 2013; Pinar et al., 2020; Seth and McGillivray, 2018). For example, when four or fewer indicators are used to construct an index, 0.15 and 0.20 lower bound weights are imposed to obtain the optimal and inferior scenario weights (see Table 5 for the results). On the other hand, when seven or more indicators or categories are used to obtain composite indices, lower bound weight of 0.05 is used (see Table 6 for results). The results align with the weights presented in Tables 3 and 4, where some indicators are allocated relatively higher (lower) weights than others.

<Insert Tables 5 and 6 approximately here>

For the second set of robustness analyses, optimal and inferior mixing weights for 2010, 2012, 2014, 2016, 2018 and 2020 are obtained when aggregate achievements in environmental health and ecosystem vitality are used. Since the indicator list under each policy objective has been changing over time, only the policy objectives are used for this analysis.[3] Table 7 provides the optimal and inferior mixing weights when a lower bound weight of 0.1 is employed. Except for 2020, the environmental health policy objective gets relatively higher importance in the optimal scenario, and ecosystem vitality gets relatively higher weights in the inferior scenario. These findings suggest that the achievements in environmental health have been relatively higher than those of ecosystem vitality until 2020. However, the findings may also have been driven by the inclusion of a new set of indicators to both environmental health and ecosystem vitality between 2018 and 2020. To test whether the inclusion of these new indicators may have driven the optimal and inferior mixing weights, one could apply the stochastic spanning test offered by Arvanitis et al. (2019).

<Insert Table 7 approximately here>

In a recent report, Papadimitriou et al. (2020) also examined the impact of varying some of the assumptions of EPI within a range of alternatives in an uncertainty analysis. In particular, they examined the sensitivity of country rankings when they allowed weights allocated to the environmental health (ecosystem vitality) to vary between 0.3 and 0.5 (0.45 and 0.75). To provide a comparison to their paper, analysis is carried out to obtain optimal and inferior mixing weights when weights are allowed to vary between these ranges. When weight allocated to environmental health is allowed to vary between 0.3 and 0.5, the optimal and inferior mixing weights are obtained when environmental health is allocated 0.3 and 0.5 weights, respectively (i.e., ecosystem vitality is allocated weights of 0.7 and 0.5, respectively). On the other hand, when weight given to ecosystem vitality is allowed to vary between 0.45 and 0.75, optimal and inferior mixing weights are obtained when ecosystem

[3] For instance, the 2018 edition of the EPI has 24 performance indicators compared to 32 indicators in the 2020 edition.

vitality is allocated 0.75 and 0.45 weights, respectively (i.e., environmental health is given weights of 0.25 and 0.55, respectively).

Using four optimal and inferior mixing weights, the maximum and minimum scores and rankings are obtained, and these are compared with the official EPI scores and rankings. Table 8 offers ten countries that experienced the highest EPI score and ranking changes with optimal and inferior mixing weights compared to the official EPI (see Appendix Table A2 for the detailed results for all the countries). EPI scores of Singapore, Iceland, Central African Republic, Ireland, Norway, Canada, Finland and Botswana changed more than 10 points with alternative weights compared to the official EPI scores. On the other hand, Qatar, Central African Republic, Maldives, Barbados, Gabon experiences more than 40 rank changes with alternative weight allocation to the environmental health and ecosystem vitality. Overall, 62 and 100 countries experienced less than 5 and 10 position changes, respectively. On the other hand, 32 countries experienced more than 20 position changes in the rankings with alternative weights. Overall, even though most countries experienced relatively minor changes in their rankings (i.e., 100 countries out of 180 countries experienced less than ten position changes), a good portion of the countries still experienced major rank changes with alternative weights allocated to the environmental health and ecosystem vitality.[4]

<Insert Table 8 approximately here>

7. Conclusions

The present study uses an existing partial order and that calls for a theoretical derivation and analysis of partial orders, which are tailor-made for environmental

[4] It should be noted that the analysis of Papadimitriou et al. (2020) only examined the weight sensitivity of rankings when they allocated alternative weights to the environmental health and ecosystem vitality; however, the rankings would be more sensitive if the weights given to the categories located under environmental health and ecosystem vitality (e.g., weights obtained in Tables 5 and 6).

performance measurements, and examined the sensitivity of the EPI of the Yale Center for Environmental Law and Policy. In particular, the optimal and inferior mixing weights are obtained, which would result in cross-country distribution of sustainability scores that 'majorizes' the distribution of every alternative weighting scheme and majorized by any alternative, respectively. The cross-country distribution of sustainability scores obtained with the optimal and inferior weights show a remarkable difference compared to the cumulative distribution of the official EPI scores (i.e., EPI scores obtained with the benchmark weights). EPI scores with the optimal (inferior) scenario have more (fewer) countries above any score, amd 37 countries experienced more than 50 point change in their composite EPI scores. Furthermore, the composite scores obtained with the optimal and inferior weights resulted in a remarkable variation in rankings, where 67 countries experienced more than 30 position changes in their rankings.

Overall, even though environmental performance indices provide a more holistic picture of the environmental achievements across countries, alterations in the normative choices made in the construction of these indices could lead to significant variations in composite scores and rankings. Therefore, if these composite indices convey messages to governments in policymaking, governments should be cautious about these indices' sensitivity based on the indicator and weight choices. Similarly, the empirical literature that utilizes environmental performance indices as an environmental quality proxy should also carry out a robustness analysis. Their robustness analysis may use indicators/categories of these composite indices as separate environmental quality proxies to ensure their empirical findings are robust to the choice of the indicators/categories used to construct these indices.

The current study obtained the weights given to the existing set of indicators; however, a new set of indicators were included in the existing set over time to measure EPI. Therefore, a future study could employ a recently developed stochastic spanning test by

Arvanitis et al. (2019) to examine whether augmentation of the indicator list resulted in cross-country distribution of sustainability scores that 'majorizes' the distribution of every alternative weighting scheme or not. Secondly, one could use newly developed stochastic bound tests by Arvanitis et al. (2021) to examine whether a given sustainability index dominates all alternative sustainability indices constructed with the existing indicators rather than dominating the benchmark composite indices. These two areas are promising future venues for providing more in-depth analysis about the sensitivity of the composite sustainability scores.

<Insert Appendix Tables A1 and A2 approximately here>

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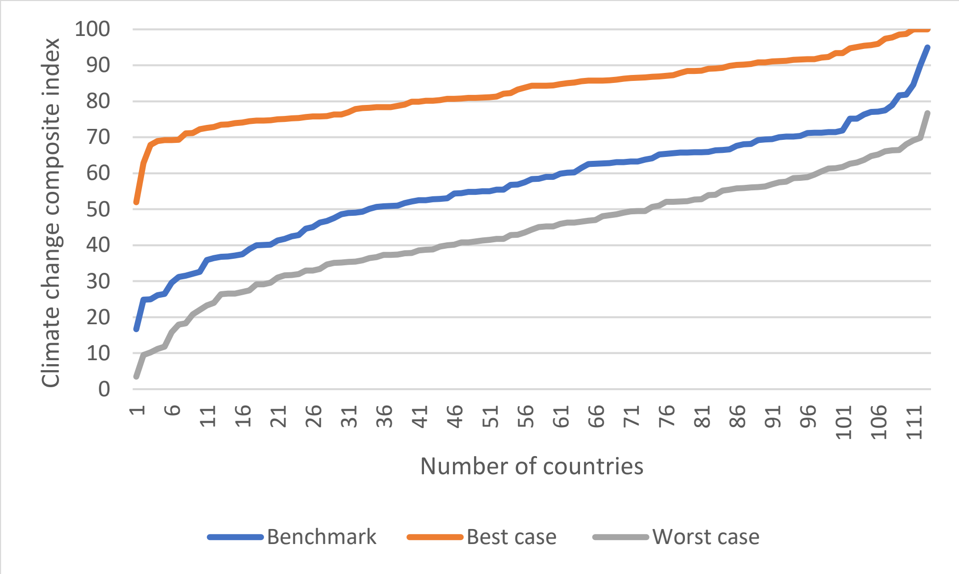

Figure 1. Cumulative composite scores with the benchmark, optimal and inferior scenarios in climate change category

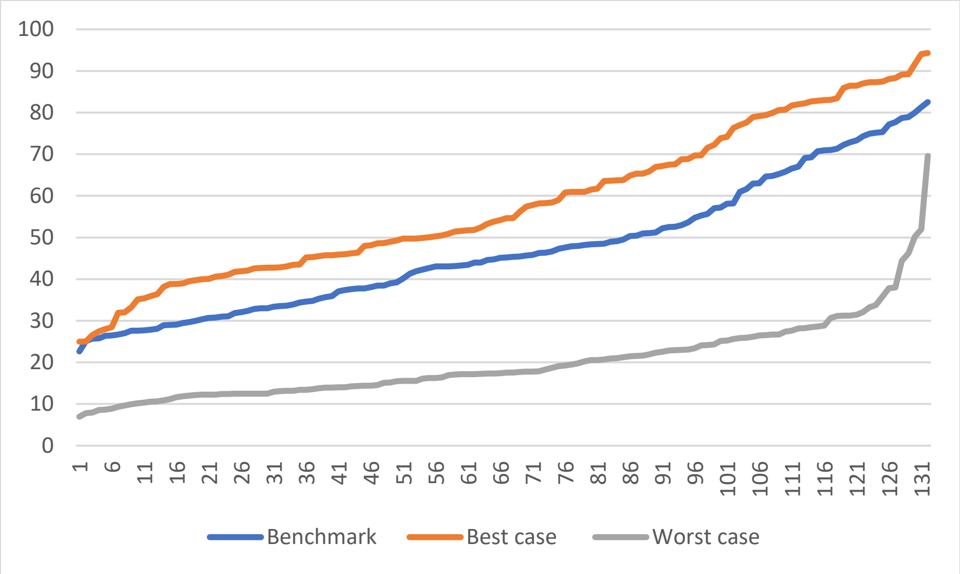

Figure 2. Cumulative EPI composite scores with the benchmark, optimal and inferior scenarios.

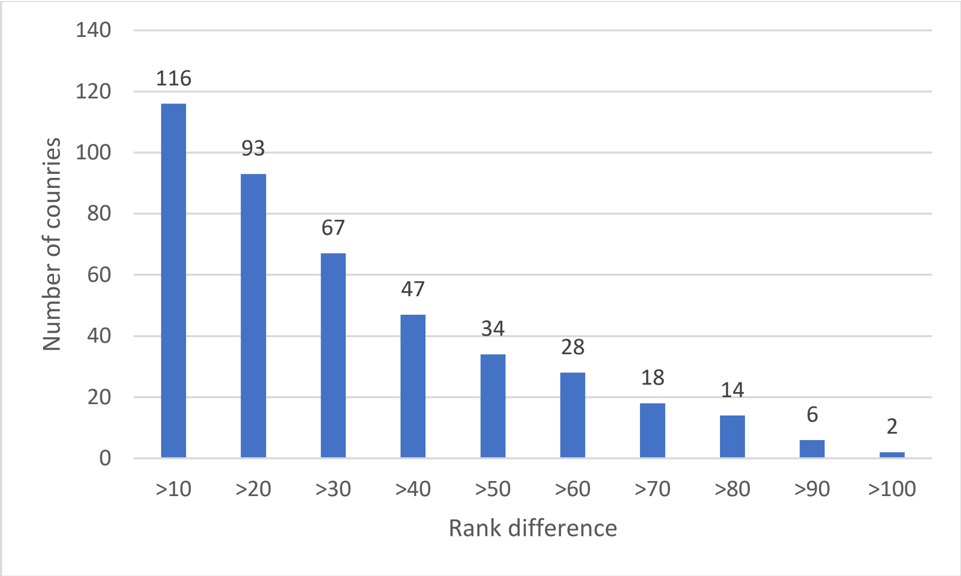

Figure 3. Distribution of rank differences above a given level between benchmark, optimal and inferior scenarios of EPI scores

Table 1. Policy objective, issue categories and indicators, and respective weights.					
Policy objective	Issue category	Category weight	Indicators	Indicator weight	Indicator weight to overall index
Environmental health (40%)	Air quality	50%	$PM_{2.5}$ exposure	55%	11%
			Household solid fuels	40%	8%
			Ozone exposure	5%	1%
	Sanitation & Drinking Water	40%	Unsafe sanitation	40%	6.4%
			Unsafe drinking water	60%	9.6%
	Heavy Metals	5%	Lead exposure	100%	2%
	Waste Management	5%	Solid waste management	100%	2%
Ecosystem vitality (60%)	Biodiversity & Habitat	25%	Terrestrial biome protection (national)	20%	3%
			Terrestrial biome protection (global)	20%	3%
			Marine protected areas	20%	3%
			Protected Areas Representativeness Index (PARI)	10%	1.5%
			Species Habitat Index (SHI)	10%	1.5%
			Species Protection Index (SPI)	10%	1.5%
			Biodiversity Habitat Index (BHI)	10%	1.5%
	Ecosystem Services	10%	Tree cover loss	90%	5.4%
			Grassland loss	5%	0.3%
			Wetland loss	5%	0.3%
	Fisheries	10%	Fish stock	35%	2.1%
			Marine Trophic Index (MTI)	35%	2.1%
			Fish caught by trawling	30%	1.8%
	Climate Change	40%	CO_2 growth rate	55%	13.2%
			CH_4 growth rate	15%	3.6%
			F-gas growth rate	10%	2.4%
			N_2O growth rate	5%	1.2%
			Black carbon growth rate	5%	1.2%
			CO_2 emissions growth from land cover	2.5%	0.6%
			GHG emissions growth rate	5%	1.2%
			GHG emissions per capita	2.5%	0.6%
	Pollution emissions	5%	SO_2 growth rate	50%	1.5%
			NO_x growth rate	50%	1.5%
	Agriculture	5%	Sustainable Nitrogen Management Index (SNMI)	100%	3%
	Water resources	5%	Wastewater treatment	100%	3%

Table 2. Descriptive Statistics

Indicator/Issue category/Policy objective	Mean	Median	SD	Min	Max	Obs.
Air quality	44.2	37.9	21.9	9.9	98.8	180
$PM_{2.5}$ Exposure	42.7	40.7	22.1	0	100	180
Household Solid Fuels	46.1	39.4	32.8	0	100	180
Ozone Exposure	46.2	41.9	21.5	0	100	180
Sanitation & Drinking Water	47.3	47.5	28.1	0	100	180
Unsafe Sanitation	50.7	51.0	29.8	0	100	180
Unsafe Drinking Water	45.1	45.1	27.5	0	100	180
Heavy metals - Lead exposure	53.0	48.2	21.7	0	100	180
Solid waste management	37.1	29.0	36.3	0	100	180
Environmental Health	45.6	43.6	23.7	11.8	99.3	180
Biodiversity & Habitat	57.6	60.5	21.9	6.5	91.6	180
Terrestrial Biome Protection (national)	66.8	78.6	33.3	0	100	180
Terrestrial Biome Protection (global)	67.6	78.4	32.8	0	100	180
Marine Protected Areas	30.6	7.0	40.4	0	100	136
Protected Areas Representativeness Index	31.3	29.2	21.0	0	98.6	180
Species Habitat Index	79.6	86.3	21.7	0	100	156
Species Protection Index	73.3	81.1	26.0	0	100	156
Biodiversity Habitat Index	54.8	52.9	12.1	23.6	82.4	180
Ecosystem Services	41.8	34.6	24.1	0	100	176
Tree Cover Loss	38.4	32.6	24.2	0	100	168
Grassland Loss	59.7	56.1	20.4	9.4	100	166
Wetland Loss	59.5	54.9	25.7	0	100	157
Fisheries	16.1	12.8	12.2	0	71.4	136
Fish Stock Status	11.6	9.8	8.5	0	36.2	111
Marine Trophic Index	19.6	15.7	17.5	0	100	124
Fish Caught by Trawling	17.3	6.5	26.7	0	100	77
Climate Change	49.8	50.9	17.1	12.1	95	180
CO_2 Growth Rate	40.6	41.5	21.3	0	100	180
CH_4 Growth Rate	64.9	65.5	26.9	0	100	180
F-gas Growth Rate	90.6	89.8	5.6	67.4	100	116
N_2O Growth Rate	56.4	59.2	25.5	0	100	180
Black Carbon Growth Rate	55.0	53.2	30.1	0	100	180
CO_2 from Land Cover	51.0	51.9	26.1	0	100	167
GHG Intensity Trend	48.8	47.8	22.6	0	100	180
GHG per Capita	50.8	54.2	28.7	0	100	180
Pollution Emissions	61.2	58.7	26.8	0	100	180
SO_2 Growth Rate	66.3	65.5	29.5	0	100	180
NO_x Growth Rate	56.0	50.9	30.4	0	100	180
Agriculture - SNMI	39.3	38.8	17.6	0	79.5	180
Water Resources - Waste water management	21.8	3.1	32.3	0	100	180
Ecosystem vitality	47.0	45.2	12.2	23.6	76.4	180
EPI	46.4	44.0	15.5	22.6	82.5	180

Table 3. Optimal and inferior scenario weights allocated to indicators in different categories									
Panel A. Air quality									
Obs.	Scenario	$PM_{2.5}$ exposure	Household solid fuels	Ozone exposure					
180	Optimal	0.086	0.369	0.545					
180	Inferior	0.733	0.189	0.078					
Panel B. Sanitation & Drinking Water									
Obs.	Scenario	Unsafe sanitation	Unsafe drinking water						
180	Optimal	0.986	0.014						
180	Inferior	0.023	0.977						
Panel C. Biodiversity & Habitat									
Obs.	Scenario	TBP-national	TBP-global	Marine protected areas	PARI	SHI	SPI	BHI	
113	Optimal	0.130	0.082	0.000	0.000	0.652	0.136	0.000	
113	Inferior	0.000	0.000	0.336	0.374	0.000	0.000	0.290	
Panel D. Ecosystem services									
Obs.	Scenario	Tree cover loss	Grassland loss	Wetland loss					
147	Optimal	0.000	0.465	0.535					
147	Inferior	1.000	0.000	0.000					
Panel E. Fisheries									
Obs.	Scenario	Fish Stock Status	Marine Trophic Index	Fish Caught by Trawling					
55	Optimal	0.082	0.714	0.204					
55	Inferior	0.839	0.000	0.161					
Panel F. Climate change									
Obs.	Scenario	CO_2 growth rate	CH_4 growth rate	F-gas growth rate	N_2O growth rate	BC growth rate	CO_2 growth Land	GHG growth rate	GHG per capita
113	Optimal	0.000	0.105	0.718	0.000	0.177	0.000	0.000	0.000
113	Inferior	0.360	0.000	0.000	0.000	0.000	0.000	0.000	0.640
Panel G. Pollution emissions									
Obs.	Scenario	SO_2 growth rate	NO_x growth rate						
180	Optimal	0.942	0.058						
180	Inferior	0.063	0.937						
Notes: Optimal and inferior scenarios offer the weights of indicators that would produce cross-country distributions of index scores that majorize the distribution of every alternative weighting scheme and are not majorized by an alternative, respectively.									

Table 4. Optimal and inferior scenario weights allocated to issue categories in environment health, ecosystem vitality and EPI

Panel A. Environmental health												
Obs.	Scenario	Air quality	Sanitation & Drinking Water	Lead exposure	Solid waste management							
180	Optimal	0.067	0.191	0.721	0.021							
180	Inferior	0.477	0.000	0.000	0.523							
Panel B. Ecosystem vitality												
	Scenario	Biodiversity & Habitat	Ecosystem Services	Fisheries	Climate Change	Pollution emissions	Agriculture	Water resources				
132	Optimal	0.345	0.000	0.000	0.130	0.525	0.000	0.000				
132	Inferior	0.000	0.073	0.707	0.000	0.000	0.084	0.136				
Panel C. Environmental Performance Index												
	Scenario	Air quality	Sanitation & Drinking Water	Lead exposure	Solid waste management	Biodiversity & Habitat	Ecosystem Services	Fisheries	Climate Change	Pollution emissions	Agriculture	Water resources
132	Optimal	0.000	0.000	0.130	0.000	0.278	0.000	0.000	0.166	0.426	0.000	0.000
132	Inferior	0.000	0.000	0.000	0.029	0.000	0.038	0.705	0.000	0.000	0.089	0.139

Notes: Notes: Optimal and inferior scenarios offer the weights of indicators that would produce cross-country distributions of index scores that majorize the distribution of every alternative weighting scheme and are not majorized by an alternative, respectively.

Table 5. Optimal and inferior scenario weights with a lower bound weight constraint

Lower bound weight	Obs.	Scenario				
Panel A. Air quality category						
Lower bound weight	Obs.	Scenario	$PM_{2.5}$ exposure	Household solid fuels	Ozone exposure	
0.15	180	Optimal	0.219	0.364	0.417	
0.15	180	Inferior	0.650	0.177	0.173	
0.20	180	Optimal	0.219	0.364	0.417	
0.20	180	Inferior	0.580	0.210	0.210	
Panel B. Sanitation & Drinking Water category						
Lower bound weight	Obs.	Scenario	Unsafe sanitation	Unsafe drinking water		
0.15	180	Optimal	0.843	0.157		
0.15	180	Inferior	0.160	0.840		
0.20	180	Optimal	0.790	0.210		
0.20	180	Inferior	0.213	0.787		
Panel C. Ecosystem services						
Lower bound weight	Obs.	Scenario	Tree cover loss	Grassland loss	Wetland loss	
0.15	147	Optimal	0.150	0.420	0.430	
0.15	147	Inferior	0.750	0.150	0.150	
0.20	147	Optimal	0.200	0.380	0.420	
0.20	147	Inferior	0.600	0.200	0.200	
Panel D. Fisheries						
Lower bound weight	Obs.	Scenario	Fish Stock Status	Marine Trophic Index	Fish Caught by Trawling	
0.15	55	Optimal	0.150	0.700	0.150	
0.15	55	Inferior	0.698	0.150	0.152	
0.20	55	Optimal	0.200	0.600	0.200	
0.20	55	Inferior	0.600	0.200	0.200	
Panel E. Pollution emissions						
Lower bound weight	Obs.	Scenario	SO_2 growth rate	NO_x growth rate		
0.15	180	Optimal	0.850	0.150		
0.15	180	Inferior	0.150	0.850		
0.20	180	Optimal	0.800	0.200		
0.20	180	Inferior	0.200	0.800		
Panel F. Environmental health						
Lower bound weight	Obs.	Scenario	Air quality	Sanitation & Drinking Water	Lead exposure	Solid waste management
0.15	180	Optimal	0.150	0.184	0.516	0.150
0.15	180	Inferior	0.275	0.150	0.150	0.425
0.20	180	Optimal	0.200	0.237	0.363	0.200
0.20	180	Inferior	0.250	0.200	0.200	0.350

Notes: Optimal and inferior scenarios offer the weights of indicators that would produce cross-country distributions of index scores that majorize the distribution of every alternative weighting scheme and are not majorized by an alternative with lower bound constraints, respectively.

Table 6. Optimal and inferior scenario weights with lower bound weight constraints

Environmental health												
Panel A. Biodiversity & Habitat												
Obs.	Scenario	TBP-national	TBP-global	Marine protected areas	PARI	SHI	SPI	BHI				
113	Optimal	0.167	0.142	0.050	0.050	0.407	0.134	0.050				
113	Inferior	0.050	0.050	0.280	0.370	0.050	0.050	0.150				
Panel B. Climate change												
Obs.	Scenario	CO_2 growth rate	CH_4 growth rate	F-gas growth rate	N_2O growth rate	BC growth rate	CO_2 growth Land	GHG growth rate	GHG per capita			
113	Optimal	0.050	0.050	0.570	0.050	0.130	0.050	0.050	0.050			
113	Inferior	0.230	0.050	0.050	0.050	0.050	0.050	0.050	0.470			
Panel C. Ecosystem vitality												
	Scenario	Biodiversity & Habitat	Ecosystem Services	Fisheries	Climate Change	Pollution emissions	Agriculture	Water resources				
132	Optimal	0.235	0.050	0.050	0.115	0.450	0.050	0.050				
132	Inferior	0.050	0.110	0.577	0.050	0.050	0.070	0.093				
Panel D. Environmental Performance Index												
	Scenario	Air quality	Sanitation & Drinking Water	Lead exposure	Solid waste management	Biodiversity & Habitat	Ecosystem Services	Fisheries	Climate Change	Pollution emissions	Agriculture	Water resources
132	Optimal	0.050	0.050	0.082	0.050	0.139	0.050	0.050	0.084	0.345	0.050	0.050
132	Inferior	0.050	0.050	0.050	0.052	0.050	0.065	0.407	0.050	0.050	0.051	0.125

Notes: Notes: Optimal and inferior scenarios offer the weights of indicators that would produce cross-country distributions of index scores that majorize the distribution of every alternative weighting scheme and are not majorized by an alternative with a lower bound weight of 0.05, respectively.

Table 7. Over-time optimal and inferior scenario weights			
Panel A. Optimal scenario weights			
Year	Observations	Environmental health	Ecosystem vitality
2010	163	0.879	0.121
2012	132	0.858	0.142
2014	178	0.896	0.104
2016	180	0.867	0.133
2018	180	0.875	0.125
2020	180	0.115	0.885
Panel B. Inferior scenario weight			
Year	Observations	Environmental health	Ecosystem vitality
2010	163	0.264	0.736
2012	132	0.131	0.869
2014	178	0.100	0.900
2016	180	0.115	0.885
2018	180	0.112	0.888
2020	180	0.850	0.150

Table 8. Ten countries that experienced EPI score and ranking changes with optimal and inferior mixing weights compared to the official EPI				
Panel A. Countries that experienced significant EPI score changes				
country	Official EPI score	Maximum EPI score	Minimum EPI score	Difference in scores
Singapore	58.12	64.84	51.40	13.44
Iceland	72.24	78.71	65.78	12.93
Central African Republic	36.98	43.18	30.79	12.39
Ireland	72.84	78.18	67.50	10.68
Norway	77.68	82.89	72.48	10.41
Canada	71.06	76.22	65.90	10.32
Finland	78.90	84.00	73.80	10.20
Botswana	40.36	45.40	35.32	10.08
Cameroon	33.58	38.58	28.59	9.99
Qatar	37.10	42.05	32.15	9.90
Panel B. Countries that experienced major rank reversals				
country	Official EPI - Ranking	Maximum EPI score - Ranking	Minimum EPI score - Ranking	Difference in ranking
Qatar	122	155	96	59
Central African Republic	124	146	96	50
Maldives	127	153	108	45
Barbados	77	104	62	42
Gabon	76	98	57	41
Uruguay	61	88	49	39
Mauritius	82	106	67	39
Viet Nam	141	161	122	39
Botswana	103	120	84	36
Uzbekistan	88	100	67	33

Table A1. Benchmark, optimal and inferior composite scores and rankings						
Country	Benchmark composite score	Optimal scenario composite score	Inferior scenario composite score	Benchmark ranking	Optimal scenario ranking	Inferior scenario ranking
Angola	29.67	25.02	14.25	115	131	90
Albania	49.00	76.98	11.64	50	30	117
United Arab Emirates	55.65	71.54	26.69	35	35	25
Argentina	52.16	58.41	12.46	42	59	108
Antigua and Barbuda	48.53	48.65	7.81	51	85	131
Australia	74.95	83.46	22.96	10	15	40
Belgium	73.32	87.31	24.06	12	10	36
Benin	29.98	42.73	13.14	114	103	99
Bangladesh	29.04	28.45	19.27	118	127	57
Bulgaria	57.03	81.69	20.68	34	22	51
Bahrain	51.01	63.68	20.59	44	49	52
Bahamas	43.46	43.06	9.62	72	100	125
Belize	41.91	42.64	17.20	80	105	71
Brazil	51.21	60.96	21.46	43	55	47
Barbados	45.65	45.17	17.54	63	97	66
Brunei Darussalam	54.75	51.61	9.93	37	73	124
Canada	71.02	82.88	26.71	16	18	24
Chile	55.26	54.62	28.23	36	66	20
China	37.34	42.82	21.21	91	101	48
Cote d'Ivoire	25.79	39.97	15.50	129	113	83
Cameroon	33.59	46.18	12.49	100	90	104
Republic of Congo	30.77	31.95	12.49	111	126	103
Colombia	52.95	60.96	20.97	39	54	50
Comoros	32.08	42.09	17.80	107	106	62
Cabo Verde	32.84	33.22	22.55	105	124	42
Costa Rica	52.51	49.89	13.91	41	79	94
Cuba	48.42	63.56	11.16	52	51	118
Cyprus	64.81	74.18	27.37	25	32	23
Germany	77.18	89.24	33.21	7	4	10
Djibouti	28.09	42.70	8.58	120	104	129
Dominica	44.57	51.81	25.59	69	71	31
Denmark	82.53	94.08	33.74	1	2	9
Dominican Republic	46.31	69.68	19.51	61	37	56
Algeria	44.75	50.90	17.87	68	75	61
Ecuador	50.98	51.77	15.13	45	72	85
Egypt	43.32	48.94	21.93	73	84	44
Eritrea	30.41	45.88	12.02	113	92	115
Spain	74.33	88.04	32.07	11	7	11
Estonia	65.28	86.49	28.86	24	12	17
Finland	78.90	86.43	31.21	4	13	14
Fiji	34.41	45.78	46.23	98	93	4
France	79.98	91.66	30.69	3	3	16

Micronesia	33.02	38.84	28.59	104	118	18
Gabon	45.79	79.96	8.68	62	25	128
United Kingdom	81.30	94.30	28.50	2	1	19
Georgia	41.30	28.03	14.05	81	128	91
Ghana	27.61	41.90	10.58	124	107	121
Guinea	26.36	38.16	13.78	128	119	95
Gambia	27.87	42.79	12.26	121	102	113
Guinea-Bissau	29.10	53.25	6.95	117	69	132
Equatorial Guinea	38.03	63.76	14.03	87	48	92
Greece	69.08	73.86	31.18	20	33	15
Grenada	43.06	41.04	17.78	77	109	63
Guatemala	31.82	40.64	15.58	108	111	81
Guyana	35.89	35.94	12.28	93	121	112
Honduras	37.79	52.44	17.26	89	70	70
Croatia	63.05	83.03	25.18	27	17	33
Haiti	27.01	27.44	15.59	125	129	80
Indonesia	37.79	46.39	15.22	88	89	84
India	27.64	35.37	17.06	123	122	74
Ireland	72.83	82.70	26.50	13	19	27
Iran	48.01	57.79	17.18	55	62	73
Iceland	72.27	59.07	17.19	14	58	72
Israel	65.83	76.31	50.18	23	31	3
Italy	70.96	77.59	27.60	17	29	22
Jamaica	48.23	66.93	7.98	54	43	130
Japan	75.16	78.93	44.35	9	28	5
Kenya	34.64	45.26	10.67	97	96	120
Cambodia	33.57	45.73	13.94	101	94	93
South Korea	66.53	82.02	28.19	22	21	21
Kuwait	53.64	68.79	22.33	38	39	43
Lebanon	45.34	49.74	21.53	65	80	46
Liberia	22.64	31.98	10.36	132	125	122
Saint Lucia	43.13	41.72	16.29	74	108	77
Sri Lanka	38.98	54.16	12.49	84	67	105
Lithuania	62.95	87.32	26.55	28	9	26
Latvia	61.62	85.92	25.94	29	14	29
Morocco	42.29	64.87	18.69	79	47	59
Madagascar	26.48	35.12	13.39	127	123	98
Maldives	35.65	24.98	37.96	94	132	6
Mexico	52.56	67.45	20.26	40	41	54
Malta	70.73	72.27	17.72	18	34	64
Myanmar	25.06	38.87	12.39	131	117	110
Montenegro	46.36	65.84	9.37	60	44	126
Mozambique	33.94	50.03	15.53	99	78	82
Mauritania	27.69	38.96	13.09	122	116	101
Mauritius	45.15	43.47	17.43	67	99	67
Malaysia	47.88	49.71	16.28	56	82	78

Namibia	40.18	65.33	10.16	82	46	123
Nigeria	31.02	58.27	12.30	110	60	111
Nicaragua	39.24	61.53	11.91	83	53	116
Netherlands	75.28	89.15	31.22	8	5	13
Norway	77.67	87.45	23.39	6	8	37
New Zealand	71.33	80.61	23.07	15	24	38
Oman	38.47	43.52	26.18	85	98	28
Pakistan	33.04	49.25	12.47	103	83	106
Panama	47.26	60.77	14.38	58	57	88
Peru	43.96	49.73	25.21	71	81	32
Philippines	38.44	58.22	14.41	86	61	87
Papua New Guinea	32.39	48.12	14.59	106	87	86
Poland	60.93	82.26	22.89	30	20	41
Portugal	67.03	79.12	35.86	21	27	8
Qatar	37.06	48.62	18.36	92	86	60
Romania	64.67	86.96	51.96	26	11	2
Russia	50.46	68.88	12.17	46	38	114
Saudi Arabia	43.97	36.40	25.87	70	120	30
Sudan	34.79	50.25	12.45	96	77	109
Senegal	30.70	51.42	13.54	112	74	96
Singapore	58.14	57.45	69.58	32	63	1
Solomon Islands	26.67	39.53	24.15	126	115	35
Sierra Leone	25.70	40.78	17.35	130	110	68
El Salvador	43.09	61.76	8.90	75	52	127
Sao Tome and Principe	37.61	47.96	17.59	90	88	65
Suriname	45.18	67.16	19.08	66	42	58
Sweden	78.71	88.31	31.48	5	6	12
Seychelles	58.16	79.35	16.97	31	26	75
Togo	29.46	50.50	12.46	116	76	107
Thailand	45.43	67.58	12.93	64	40	102
Timor-Leste	35.27	53.84	37.81	95	68	7
Trinidad and Tobago	47.56	69.68	10.89	57	36	119
Tunisia	46.68	60.92	23.04	59	56	39
Turkey	42.64	56.16	19.76	78	64	55
Taiwan	57.19	80.71	17.34	33	23	69
Tanzania	31.11	45.51	14.35	109	95	89
Ukraine	49.55	63.61	21.04	48	50	49
Uruguay	49.11	39.77	13.45	49	114	97
United States of America	69.29	83.08	21.66	19	16	45
Saint Vincent and the Grenadines	48.37	45.97	20.56	53	91	53
Venezuela	50.36	54.63	13.14	47	65	100
Viet Nam	33.36	40.04	16.10	102	112	79
Vanuatu	28.93	26.57	24.35	119	130	34
South Africa	43.06	65.33	16.37	76	45	76

Table A2. Maximum and minimum EPI scores and rankings with optimal and inferior mixing weights compared to the official EPI scores and rankings								
Country	EPI score	Max score	Min score	Δ EPI Scores	EPI - Rank	Max - Rank	Min - Rank	Δ Rank
Afghanistan	25.52	26.90	24.14	2.76	178	179	176	3
Albania	49.00	50.13	47.88	2.25	62	70	59	11
Algeria	44.76	46.17	43.35	2.82	84	94	78	16
Angola	29.70	32.03	27.38	4.65	158	159	157	2
Antigua and Barbuda	48.48	50.24	46.73	3.51	63	71	59	12
Argentina	52.16	54.17	50.15	4.02	54	58	48	10
Armenia	52.26	54.45	50.07	4.38	53	60	44	16
Australia	74.92	79.09	70.75	8.34	13	16	12	4
Austria	79.60	81.70	77.50	4.20	6	9	5	4
Azerbaijan	46.50	49.95	43.05	6.90	72	92	61	31
Bahamas	43.44	45.86	41.03	4.83	93	110	79	31
Bahrain	51.00	51.45	50.55	0.90	56	59	52	7
Bangladesh	29.06	30.73	27.40	3.33	162	163	156	7
Barbados	45.64	49.41	41.88	7.53	77	104	62	42
Belarus	53.02	53.74	52.30	1.44	49	50	49	1
Belgium	73.28	76.46	70.10	6.36	15	17	17	0
Belize	41.92	42.33	41.52	0.81	101	101	97	4
Benin	29.96	32.38	27.55	4.83	157	157	154	3
Bhutan	39.34	41.73	36.96	4.77	107	113	105	8
Bolivia	44.24	46.33	42.16	4.17	89	95	74	21
Bosnia and Herzegovina	45.40	45.78	45.03	0.75	80	81	79	2
Botswana	40.36	45.40	35.32	10.08	103	120	84	36
Brazil	51.20	51.58	50.83	0.75	55	56	51	5
Brunei Darussalam	54.80	59.60	50.00	9.60	46	60	39	21
Bulgaria	57.02	58.70	55.34	3.36	41	44	39	5
Burkina Faso	38.38	43.08	33.69	9.39	112	126	98	28
Burundi	27.06	28.35	25.77	2.58	170	171	165	6
Cabo Verde	32.86	33.48	32.25	1.23	144	146	136	10
Cambodia	33.56	34.33	32.80	1.53	140	140	132	8
Cameroon	33.58	38.58	28.59	9.99	139	150	121	29
Canada	71.06	76.22	65.90	10.32	20	27	18	9
Central African Republic	36.98	43.18	30.79	12.39	124	146	96	50
Chad	26.72	29.68	23.77	5.91	172	179	166	13
Chile	55.24	57.28	53.20	4.08	44	46	41	5
China	37.36	38.47	36.25	2.22	120	134	110	24
Colombia	52.96	53.47	52.45	1.02	50	52	48	4
Comoros	32.10	33.30	30.90	2.40	148	150	145	5
Costa Rica	52.52	54.52	50.53	3.99	52	56	47	9
Cote d'Ivoire	25.82	27.43	24.22	3.21	176	176	175	1
Croatia	63.06	63.53	62.60	0.93	34	34	29	5
Cuba	48.40	48.93	47.88	1.05	65	69	64	5
Cyprus	64.82	68.99	60.65	8.34	31	37	29	8
Czech Republic	71.06	71.75	70.37	1.38	20	26	12	14

Dem. Rep. Congo	36.38	39.88	32.89	6.99	125	131	115	16
Denmark	82.52	84.82	80.23	4.59	1	3	1	2
Djibouti	28.08	30.08	26.09	3.99	164	165	163	2
Dominica	44.58	45.14	44.03	1.11	86	90	80	10
Dominican Republic	46.36	48.93	43.80	5.13	74	90	65	25
Ecuador	50.98	51.18	50.79	0.39	57	57	55	2
Egypt	43.34	45.73	40.96	4.77	94	99	81	18
El Salvador	43.10	43.25	42.95	0.30	96	95	94	1
Equatorial Guinea	38.10	40.73	35.48	5.25	115	117	111	6
Eritrea	30.44	34.18	26.71	7.47	156	161	143	18
Estonia	65.26	67.20	63.33	3.87	30	31	30	1
Eswatini	33.80	37.85	29.75	8.10	137	149	126	23
Ethiopia	34.44	36.75	32.13	4.62	134	137	131	6
Fiji	34.40	34.48	34.33	0.15	135	140	123	17
Finland	78.90	84.00	73.80	10.20	7	8	4	4
France	79.98	82.86	77.10	5.76	5	8	6	2
Gabon	45.84	50.33	41.36	8.97	76	98	57	41
Gambia	27.82	29.43	26.22	3.21	166	170	162	8
Georgia	41.34	42.00	40.68	1.32	102	103	100	3
Germany	77.18	80.29	74.08	6.21	10	10	7	3
Ghana	27.60	29.48	25.73	3.75	169	169	167	2
Greece	69.08	71.96	66.20	5.76	25	25	23	2
Grenada	43.06	43.87	42.25	1.62	97	101	89	12
Guatemala	31.82	32.08	31.57	0.51	149	156	138	18
Guinea	26.34	28.28	24.41	3.87	175	174	173	1
Guinea-Bissau	29.08	32.58	25.59	6.99	161	169	152	17
Guyana	35.90	36.50	35.30	1.20	126	133	121	12
Haiti	27.02	28.33	25.72	2.61	171	172	168	4
Honduras	37.78	38.88	36.69	2.19	117	120	114	6
Hungary	63.64	66.03	61.26	4.77	33	36	25	11
Iceland	72.24	78.71	65.78	12.93	17	28	14	14
India	27.64	30.48	24.81	5.67	168	173	163	10
Indonesia	37.82	40.03	35.62	4.41	116	117	114	3
Iran	48.00	48.08	47.93	0.15	67	68	68	0
Iraq	39.44	39.46	39.43	0.03	106	118	105	13
Ireland	72.84	78.18	67.50	10.68	16	20	15	5
Israel	65.84	70.28	61.40	8.88	29	36	27	9
Italy	70.98	74.61	67.35	7.26	22	21	20	1
Jamaica	48.20	48.88	47.53	1.35	66	71	65	6
Japan	75.18	78.96	71.40	7.56	12	13	11	2
Jordan	53.38	54.69	52.08	2.61	48	51	45	6
Kazakhstan	44.70	45.68	43.73	1.95	85	91	81	10
Kenya	34.64	36.88	32.41	4.47	133	135	129	6
Kiribati	37.66	41.35	33.97	7.38	118	124	107	17
Kuwait	53.64	54.56	52.73	1.83	47	48	45	3
Kyrgyzstan	39.76	41.28	38.25	3.03	105	111	108	3

Laos	34.82	36.73	32.92	3.81	130	133	130	3
Latvia	61.60	62.50	60.70	1.80	36	37	34	3
Lebanon	45.42	47.34	43.50	3.84	79	93	72	21
Lesotho	28.00	32.05	23.95	8.10	165	178	157	21
Liberia	22.68	23.03	22.34	0.69	180	180	180	0
Lithuania	62.90	62.98	62.83	0.15	35	34	32	2
Luxembourg	82.28	84.86	79.70	5.16	2	2	2	0
Madagascar	26.48	27.58	25.39	2.19	174	175	170	5
Malawi	38.32	41.28	35.37	5.91	113	119	108	11
Malaysia	47.90	49.78	46.03	3.75	68	77	61	16
Maldives	35.64	38.73	32.55	6.18	127	153	108	45
Mali	29.40	31.88	26.93	4.95	160	161	159	2
Malta	70.74	74.58	66.90	7.68	23	23	21	2
Marshall Islands	30.80	31.25	30.35	0.90	152	164	143	21
Mauritania	27.68	29.60	25.76	3.84	167	167	166	1
Mauritius	45.18	48.89	41.48	7.41	82	106	67	39
Mexico	52.54	53.80	51.28	2.52	51	54	45	9
Micronesia	33.02	33.58	32.47	1.11	142	145	133	12
Moldova	44.40	44.70	44.10	0.60	87	89	84	5
Mongolia	32.22	33.38	31.07	2.31	147	148	144	4
Montenegro	46.34	46.43	46.25	0.18	75	76	75	1
Morocco	42.30	44.55	40.05	4.50	100	103	87	16
Mozambique	33.92	35.38	32.47	2.91	136	138	133	5
Myanmar	25.08	25.20	24.96	0.24	179	179	172	7
Namibia	40.20	44.63	35.78	8.85	104	115	86	29
Nepal	32.70	35.63	29.78	5.85	145	148	137	11
Netherlands	75.28	79.21	71.35	7.86	11	14	11	3
New Zealand	71.32	75.49	67.15	8.34	19	22	19	3
Nicaragua	39.24	39.48	39.00	0.48	108	119	106	13
Niger	30.78	34.20	27.36	6.84	153	158	142	16
Nigeria	31.00	35.28	26.73	8.55	151	160	139	21
North Macedonia	55.36	58.30	52.42	5.88	43	53	40	13
Norway	77.68	82.89	72.48	10.41	9	11	7	4
Oman	38.48	39.71	37.25	2.46	110	128	105	23
Pakistan	33.02	37.63	28.42	9.21	142	151	127	24
Panama	47.28	48.06	46.50	1.56	70	72	69	3
Papua New Guinea	32.42	33.43	31.42	2.01	146	147	140	7
Paraguay	46.44	46.53	46.35	0.18	73	75	73	2
Peru	43.96	44.25	43.68	0.57	90	91	87	4
Philippines	38.48	39.58	37.39	2.19	110	117	111	6
Poland	60.94	61.45	60.43	1.02	37	38	35	3
Portugal	67.02	71.12	62.93	8.19	27	31	25	6
Qatar	37.10	42.05	32.15	9.90	122	155	96	59
Republic of Congo	30.76	33.93	27.60	6.33	154	154	144	10
Romania	64.64	68.30	60.98	7.32	32	36	19	17
Russia	50.48	51.11	49.85	1.26	58	62	55	7

Rwanda	33.76	36.10	31.42	4.68	138	141	135	6
Saint Lucia	43.12	44.29	41.95	2.34	95	103	86	17
Saint Vincent & Grenadines	48.42	49.50	47.34	2.16	64	72	62	10
Samoa	37.30	38.58	36.03	2.55	121	136	109	27
Sao Tome and Principe	37.64	39.88	35.41	4.47	119	120	116	4
Saudi Arabia	43.96	44.77	43.15	1.62	91	97	83	14
Senegal	30.72	33.30	28.14	5.16	155	153	149	4
Serbia	55.24	57.10	53.38	3.72	44	52	41	11
Seychelles	58.18	60.03	56.34	3.69	38	42	38	4
Sierra Leone	25.76	27.43	24.10	3.33	177	178	177	1
Singapore	58.12	64.84	51.40	13.44	39	53	32	21
Slovakia	68.26	69.25	67.27	1.98	26	30	18	12
Slovenia	72.02	72.80	71.24	1.56	18	24	10	14
Solomon Islands	26.70	28.28	25.13	3.15	173	173	171	2
South Africa	43.04	46.03	40.06	5.97	98	102	77	25
South Korea	66.52	70.24	62.80	7.44	28	33	27	6
Spain	74.32	77.44	71.20	6.24	14	16	14	2
Sri Lanka	38.98	39.76	38.20	1.56	109	123	104	19
Sudan	34.78	38.28	31.29	6.99	131	142	122	20
Suriname	45.18	47.33	43.04	4.29	81	93	70	23
Sweden	78.72	83.64	73.80	9.84	8	8	6	2
Switzerland	81.50	84.88	78.13	6.75	3	4	1	3
Taiwan	57.16	57.67	56.65	1.02	40	42	40	2
Tajikistan	38.22	42.60	33.84	8.76	114	125	99	26
Tanzania	31.06	31.98	30.15	1.83	150	159	147	12
Thailand	45.46	46.20	44.73	1.47	78	85	77	8
Timor-Leste	35.26	36.85	33.67	3.18	129	130	127	3
Togo	29.48	32.75	26.21	6.54	159	163	151	12
Tonga	45.04	45.40	44.68	0.72	83	85	82	3
Trinidad and Tobago	47.58	49.34	45.83	3.51	69	79	64	15
Tunisia	46.68	47.31	46.05	1.26	71	77	73	4
Turkey	42.66	44.82	40.50	4.32	99	113	82	31
Turkmenistan	43.86	44.15	43.58	0.57	92	93	88	5
Uganda	35.60	38.08	33.13	4.95	128	130	123	7
Ukraine	49.54	49.68	49.41	0.27	60	63	61	2
United Arab Emirates	55.62	55.73	55.52	0.21	42	44	43	1
United Kingdom	81.26	83.87	78.65	5.22	4	5	3	2
United States of America	69.30	72.68	65.93	6.75	24	27	22	5
Uruguay	49.10	53.75	44.45	9.30	61	88	49	39
Uzbekistan	44.34	48.00	40.68	7.32	88	100	67	33
Vanuatu	28.92	29.48	28.37	1.11	163	169	152	17
Venezuela	50.34	51.30	49.38	1.92	59	64	54	10
Viet Nam	33.34	35.16	31.53	3.63	141	161	122	39
Zambia	34.74	38.18	31.31	6.87	132	141	124	17
Zimbabwe	37.02	40.65	33.39	7.26	123	128	112	16