A measure of well-being productivity based on the World Happiness Report*

PRELIMINARY DRAFT. Please, do not quote without authors' consent.

Francesco Sarracino[a] and Kelsey J. O'Connor [b]

November 5, 2021

*This article reflects the views of the authors and does not engage in any way STATEC, and funding partners. The authors wish to thank Golnaz Amjadi, Charles Henri DiMaria, and Chiara Peroni for their helpful comments on earlier versions of this work. The authors gratefully acknowledge the support of the Observatoire de la Compétitivité, Ministère de l'Economie, DG Compétitivité, Luxembourg and STATEC.

[a]Institut national de la statistique et des études économiques du Grand-Duché du Luxembourg (STATEC Research), 14, rue Erasme, L-2013, Luxembourg. Tel.: +352 247 88469; e-mail: Francesco.Sarracino@statec.etat.lu

[b]Institut national de la statistique et des études économiques du Grand-Duché du Luxembourg (STATEC Research), Luxembourg.

Abstract

We propose a measure of well-being efficiency to assess countries' ability to transform inputs into subjective well-being. To this purpose, we use as inputs six factors (real GDP per capita, healthy life expectancy, social support, freedom of choice, absence of corruption, and generosity) identified in the World Happiness Reports. Our measure of output is subjective well-being, as measured by the Cantril ladder. By applying Data Envelopment Analysis to a sample of 74 countries, we show that it is possible to derive a measure of well-being efficiency that goes beyond income. Efficiency scores reveals that high ranking subjective well-being countries, such as the Nordics, are not strictly the most efficient. Moreover, the scores provide some insights on the origins of countries' inefficiency (scale vs technical inefficiency). Most importantly, we find that our index correlates negatively with economic efficiency. This suggests that the countries that are most successful in turning capital and labor into gross domestic product are not better at transforming their resources in subjective well-being. We regard present work as a proof-of-concept as there are various limits that we will try to overcome in coming months.

Keywords: subjective well-being, World Happiness Report, efficiency, Data Envelopment Analysis.

1 Introduction

Traditional economic thinking elevated GDP per capita to the single-most important indicator of quality of life. However, evidence has accumulated over recent decades that demonstrates economic growth does not necessarily improve people's lives and, when prioritized and mismanaged, it may even contribute negatively (Sarracino and O'Connor, 2021a,b). This evidence invites us to expand our focus, from the singular dimension of economic output towards a more holistic concept of quality of life. Indeed, it has now been more than 12 years since international institutions, backed by authoritative thinkers, have called upon us to go "beyond GDP" to conceptualize and measure well-being (e.g., Fleurbaey (2009); Stiglitz et al. (2009)). Which measures could support such a shift? Which output should be maximized? We propose to use subjective well-being (SWB), a single measure summarizing the many economic and non-economic aspects of what makes a life worth living. Numerous studies make the case for SWB (e.g., Helliwell et al. (2013); OECD (2013), but little is known about how to efficiently promote well-being, and without this knowledge, policy makers are unable to knowledgeably contrast policy alternatives.

Our aim is to provide a measure of well-being efficiency that goes beyond income. Such a measure has significant advantages over traditional efficiency measures: it indicates how well countries transform inputs into SWB, a valid and reliable measure of how people fare with their lives as a whole. SWB reflects more than just economic concerns, including health for instance, and captures how people fare with their lives as a whole. The idea that SWB can be produced more or less efficiently, and that this efficiency can be measured is relatively novel. The value added of our contribution is to show that it is possible and meaningful to compute such well-being efficiency scores. The scores can inform policy-makers about how well their countries transform available endowments in SWB, and could help identifying sources of inefficiency. Current SWB policy advice generally discusses the amount of inputs, not how well they are used. This is a pre-requisite to inform policies seeking to efficiently mobilize resources to improve well-being.

Much of the economics of happiness literature has focused on the determinants of SWB. In the series of World Happiness Reports (WHRs), six factors explain about three-quarters of the variation in SWB around the world (real GDP per capita, healthy life expectancy, having someone to count on, perceived freedom to make life choices, freedom from corruption, and generosity) (Helliwell et al., 2013). The residual 25 percent is not well explained. We do know certain groups of countries have higher or lower than expected SWB, given their observable characteristics – for instance, Latin America and post-communist states – but little is known about why. Perhaps there are important omitted variables, or perhaps Latin American countries are more efficient in transforming their inputs into well-being? For the purposes of this paper, we take for granted the WHR framework, and instead focus on answering the latter question, which has not yet been systematically assessed.

We compare 74 countries based on the efficiency in which they turn inputs into SWB. To compute efficiency, we use as inputs the six determinants of SWB identified in the WHRs, as output SWB, and Data Envelopment Analysis (DEA). DEA is a non-parametric frontier technique that is widely used to compute productive efficiency and total factor productivity in management and economic studies (see, for instance, Lafuente et al. (2016)). Efficiency is then measured as the "distance" in output from a best-practice frontier (or efficient frontier). This allows us to identify under-performing countries and leading examples.

DEA emerged as a widely used method to measure efficiency across various disciplines (Emrouznejad and liang Yang, 2018; Rostamzadeh et al., 2021). It has been applied to study efficiency in sectors such as banking, health care, agriculture, transportation, education, and – more recently – energy and environment, as well as finance (Liu et al., 2013). However, the application of DEA to SWB research is rather new. The term "happiness efficiency" was coined by Binder and Broekel (2012) in a seminal work about individuals' ability to convert resources into SWB. Debnath and Shankar (2014) used data from the World Happiness Database to study how various indicators of good governance translate into happiness efficiency. The authors used a cross-sectional dataset comprising 130 countries. Carboni and Russu (2015) proposed a similar approach to compute how efficiently Italian regions transform their inputs into SWB. Most other studies applied DEA to produce synthetic indicators of quality of life (see, for instance, Murias et al. (2006), Bernini et al. (2013), Guardiola and Picazo-Tadeo (2014), Mariano et al. (2015), and Nissi and Sarra (2018). A notable exception is the work by DiMaria et al. (2020) who applied DEA to establish whether SWB is an input or an output of economic production process in a sample of European countries. The results indicate that, in most cases, SWB can be regarded as an input to production, but it is seldom an output. This suggests that SWB contributes meaningfully to productivity, and that SWB is not a result of the production process. Using partial frontier approach, Nikolova and Popova (2021) studied country efficiency in transforming a set of inputs (income, education, and health) into SWB using panel data on 91 countries. They found that it is possible to compute well-being efficiency gains, and that low SWB efficiency is associated to unemployment and involuntary part-time employment, while social support, freedom, and the rule of law positively contribute to efficiency. Our work contributes to the ideas put forward by Debnath and Shankar (2014) and Nikolova and Popova (2021). The main difference with respect to previous works is that we propose a measure of well-being efficiency based on the WHR framework relating SWB to a set of inputs (Helliwell et al., 2013). This aspect is not trivial as it offers theoretical guidance to put in relation inputs and output. Moreover, we consider variable returns to scale, which permit to distinguish technical from scale efficiency – thus providing finer information about what countries can do to improve their efficiency. Also, we try to account for the likely different ability of people to report their well-being based on culture, genetics, and educational attainment. Finally, we contrast our measures of well-being efficiency with measures of economic efficiency and of sustainable well-being.

DEA allows researchers to model production activities without the need to specify the functional form of the production process; thus, allowing the data to reveal how different countries combine their inputs more or less efficiently to generate SWB. Typical regression approaches assume inputs are additively separable, and do not test for interactions or thresholds. Regression residuals, for Latin America for instance, mechanically represent an unknown input that enters additively. On the other hand, plausibly, a minimum level of GDP per capita and healthy life expectancy are necessary to enjoy social relations; that is, input importance is non-linear and co-dependant (Binder and Broekel, 2012). As specifying a correct functional form is problematic, parametric methods can lead to errors including wrongly identifying countries as efficient (Ravallion, 2005).

Example findings are illustrative. The ranking based on efficiency scores reveals sometimes surprising success stories. The typically high ranking SWB countries, such as the Nordics, are not strictly the most efficient. The most efficient countries includes Finland, but also, Kyrgystan, Italy, Colombia, Guatemala, and Tunisa. The results also reveal the countries that could improve, such as Bulgaria and India. In general, efficiency scores are correlated with SWB – Zimbabwe experiences the lowest efficiency and SWB, but there are other contrasting examples. Estonia and Hungary report a similar level of SWB, but the latter has lower inputs and is more efficient. We likewise correlate efficiency scores with inputs, finding GDP per capita and healthy life expectancy correlate strongly. Countries with greater productive capacity and better health are indeed better able to exploit their inputs. This finding implies policy makers might want to invest in better health not only for the direct benefits it brings for SWB, but also for the indirect effects that result from a more efficient use of inputs. DEA analysis also reveals whether countries exhibit increasing, decreasing, or constant returns to scale. Returns to scale indicate whether countries could increase their efficiency with more or less inputs. The most efficient countries exhibit constant returns to scale. It is also worth emphasizing that high efficiency does not imply high well-being: a country characterized by low levels of well-being may still use its inputs efficiently. Our results are particularly relevant and promising for less-developed countries, who have fewer economic resources to invest, but even the Nordic countries could generally use their resources relatively more efficiently. Finally, we find that our index of well-being efficiency correlates negatively with economic efficiency (GDP over capital and labor). This suggests that countries that are better equipped to transform their resources in well-being are not the same that are better at achieving economic efficiency.

The paper is organized as follows. In the next section we describe the data we use in the analysis, and in section 3 we detail the methods we adopt. Section 4 reports our findings: we first describe the efficiency scores, we then try to explain the scores across countries, and we finally compare our scores with third-party measures of SWB and usual productivity measures. The last section summarizes our findings, discusses the limitations of present work, and offers some suggestions about the usefulness of measures of well-being productivity.

2 Data

Aggregate SWB data are available for approximately 150 countries in the WHRs. The particular measure of SWB is the Cantril Ladder obtained from the Gallup World Poll, which is similar to life satisfaction. We use the most recent report, which provides SWB scores by country averaged over the years 2018-2019 (Helliwell et al., 2021). Data on the six inputs are also contained in the WHRs which, in turns uses various sources: GDP per capita (constant international dollars of 2011, converted in logarithm) is drawn from the World Development Indicators. Healthy life expectancy at birth is from the World Health Organization's Global Health Observatory data. The four remaining variables are based on survey questions from the Gallup World Poll: social support (or having someone to count on in times of trouble) is the national share of people answering positively to the question: "if you were in trouble, do you have relatives or friends you can count on to help you whenever you need them, or not?"; freedom of choice is the national share of people answering positively to the question: "are you satisfied or dissatisfied with your freedom to choose what you do with your life?"; absence of corruption is the negative of the average of the national shares of people answering to positively to two questions: first, "is corruption widespread throughout the government or not?", and second, "is corruption widespread within businesses or not?" Whenever data for government corruption are missing, only the perception of business corruption is used. Finally, generosity is the residual of regressing the national average of responses to the question "have you donated money to a charity in the past month?" on GDP per capita. Therefore, it reflects people's generosity independently from the wealth of the country they reside in. Being a residual, generosity takes both positive and negative values. However, the DEA model we use can not handle negative values. Therefore, we transformed generosity by subtracting from each score the minimum value of generosity. This transformation shifts the variable to start on zero without altering the original scale of the variable.

As discussed in the methods section below, we create groups of homogeneous countries based on three variables: culture zones (Welzel, 2013), educational atteinment (Barro et al., 2021), and genetic distance (Spolaore and Wacziarg, 2018). The rationale for grouping the countries is to compare culturally and genetically homogeneous countries in the way they conceive of well-being. Our assumption is that these three variables affect individuals' understanding and reporting of SWB (Schimmack, 2008; De Neve et al., 2012; Lykken and Tellegen, 1996). Specifically, we focus on factors that affect the way in which people understand, determine, and communicate their evaluations of well-being. Individuals have little influence over the culture and genetic composition of the countries in which they were raised. Likewise, the aggregate level of education in a country depends more on institutional characteristics and history than the present level of satisfaction.

Culture zone breaks countries into ten groups, largely based on geography, history (including colonization and experience with communism), and religion. To see a list and basic group characteristics, see Appendix D.

Genetic distance (Spolaore and Wacziarg, 2018) represents how similar the genetic make-up of individuals in a country is to that of the United States. More precisely, the expected difference between two randomly selected individuals, one from a particular country, and the second from the United States. An earlier paper by the same authors discusses the interpretation of this variable and its role in economic development at length (Spolaore and Wacziarg, 2013). The authors clarify that genetic distance does not measure particular genetic traits, but the time since two population groups shared the same ancestor – meaning, the effects of genetic distance do not represent genetic effects, but the effects of intergenerationally transferred traits (including culture). The first measures of genetic distance were created in 1990s using various genetic markers. Significant developments have occurred since then allowing for greater precision and coverage. The current data set draws upon genetic distance defined for genetic groups which are then matched to countries using data on countries' ethnic compositions. The final measure uses a weighted average for groups within a country.

Educational attainment is measured as the average years of schooling for the population aged 15 to 64, obtained from Barro et al. (2021). To create the data set the authors draw upon data from the United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute for Statistics, United Nations (UN) demographic yearbook, Eurostat, Organisation for Economic Co-operation and Development (OECD), and national statistics agencies. Building on Barro and Lee (2013), these data also account for school enrollment ratios, drop-out ratio, and the population structure to create one of the most comprehensive data sets on educational attainment. Table 1 provides summary statistics for the variables included in present study. Data availability for culture zones restricts our sample to 76 countries. Our final sample consists of 74 countries with complete information on inputs and output.

Table 1: Descriptive statistics

Variable	*mean*	*sd*	*min*	*max*	*obs*
Cantril ladder	5.662	1.166	2.375	7.780	107
GDP per capita PPP US$ 2011	9.534	1.150	6.966	11.65	107
Social support (x 10)	8.195	1.239	4.200	9.645	107
Healthy life expectancy at birth	65.74	6.551	48.70	77.10	107
Freedom of choice (x 10)	8.111	1.075	3.851	9.633	107
Generosity (x 10)	2.686	1.567	0	8.498	107
Absence of corruption (x 10)	2.802	1.969	0.459	9.304	107
Weighted genetic distance to U.S. SW 2018	0.0279	0.0146	0	0.0513	104
Culture Zone	5.368	2.832	1	10	76
Years of schooling	9.314	2.738	2.427	12.88	107

3 Methods

To compute well-being productivity, we use Data Envelopment Analysis (DEA), a technique that uses non-parametric linear programming to measure the relative performance of a group of organizational units, such as countries. Compared to other methods to compute efficiency, such as stochastic frontier analysis or ratio analysis, DEA requires no specific functional form, accommodates multiple inputs, and is not affected by problems of multicollinearity and heteroscedasticity (Tigga and Mishra, 2015). The aim of DEA models, the two basic ones are the CCR model (Charnes et al., 1978) and the BCC model (Banker et al., 1984), is to compute an envelopment frontier so that all countries lie on or below the best-practice frontier (or efficient frontier). Countries located on the frontier receive an efficiency score equal to 1 and they are regarded as efficient units. Countries located below the frontier receive a score relative to their distance from the frontier. The further they are, the lower the score, the more countries are regarded as inefficient.

Charnes et al. (1978) define efficiency as: "the maximum of a ratio of weighted outputs to weighted inputs subject that the similar ratios for every DMU be less or equal to unity". Efficiency can be described as follows:

$$TE_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \tag{1}$$

where:

TE_k is the technical efficiency of country k using m inputs to produce s outputs;

y_{rk} is the quantity of output r produced by country k;

x_{ik} is the quantity of input i used by country k;

u_r is the weight of output r;

v_i is the weight of input i;

n is the number of countries included in the analysis;

s is the number of outputs (in present case, SWB);

m is the number of inputs.

Technical efficiency of country k is maximized subject to the following constraints: first, the weights applied to inputs and output of country k cannot generate an efficiency score greater than unity (see eq. 2); second, the weights are strictly positive (see eq. 3).

$$\frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1 \qquad j = 1, \ldots, n \tag{2}$$

$$u_r, v_i > 0 \quad \forall r = 1, \ldots, s; i = 1, \ldots, m. \tag{3}$$

We assume that the aim of a country is to maximize output, i.e. SWB, given the available level of inputs. Thus, we solve the linear program above using the output-orientated DEA model. We also assume that countries operate under variable returns to scale (VRS) (Banker et al., 1984).

A common assumption in DEA models is that DMUs operate under constant returns to scale (CRS) (Charnes et al., 1978). In present case this implies assuming that all countries operate at an optimal scale. In such a situation, an input increase by 1% results in a proportional increase in the output. As we consider a wide variety of countries from all over the world, it is likely that they are not all operating at an optimal scale (Carboni and Russu, 2015). The VRS model, on the contrary, allows for countries to operate at various levels of scale efficiency, and it produces measures of TE that are not confounded by scale efficiencies (Coelli et al., 2005). The VRS model provides efficiency scores known as variable returns to scale technical efficiency (VRSTE). This is opposed to constant variable returns to scale technical efficiency, also known as 'total' efficiency. The term 'total' refers to the fact that it is composed of 'pure' technical efficiency, i.e. VRSTE, and a scale efficiency (SE).

The primal equation of the output-orientated VRS model is as follows:

$$Minimize \qquad \sum_{i=1}^{m} v_i x_{ik} - c_k \tag{4}$$

where c_k is a measure of returns to scale for country k.
Subject to:

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - c_k \geq 0 \qquad j = 1, \ldots, n \tag{5}$$

$$\sum_{r=1}^{s} u_r y_{rk} = 1 \tag{6}$$

$$u_r, v_i, c_k > 0 \qquad \forall r = 1, \ldots, s; i = 1, \ldots, m. \tag{7}$$

Comparing countries against a common frontier of best-practices is possible under the assumption that countries have similar "production technologies" to transform resources into SWB. It is difficult to test this assumption. However, as discussed in section 2, it is plausible that people around the world have different ways to report their well-being. This could affect the comparability of SWB scores across countries. To overcome this difficulty, we conduct the analysis on sub-groups of homogeneous countries. This within-group approach also accounts for cultural differences that might otherwise confound productivity differences across culturally distinct groups.

Groups are identified using hierarchical cluster analysis, a statistical technique to group statistical units with similar characteristics: culture zones, genetic distance, and years of schooling. Various algorithms are available to identify groups of similar countries. Here we use Ward's method with Gower distance. The Ward's method (Ward Jr, 1963) aggregates units that are "similar enough" by minimizing within-group variance. Two countries are set to belong to the same group if the variance associated to their grouping is small. We use the Gower distance (Gower, 1971) to compute a measure of similarity among countries based on a mix of categorical and quantitative variables.

The formula to compare an arbitrary number of variables using the Gower distance is:

$$G = \frac{\sum_i \delta_{iuv} d_{iuv}}{\sum_i \delta_{iuv}} \tag{8}$$

where u and v are two variables, δ_{iuv} is a dummy equal 1 if u and v are not missing for observation i, and 0 otherwise. If at least one variable v is continuous,

$$d_{iuv} = \frac{|x_{iu} - x_{iv}|}{\{max_v(x_{iv}) - min_v(x_{iv})\}} \tag{9}$$

d_{iuv} is set to 0 if $max_v(x_{iv}) - min_v(x_{iv}) = 0$. The Gower distance G is scaled in a numerical range of 0 (identical) and 1 (maximally dissimilar).

4 Results

4.1 Identifying groups of homogeneous countries

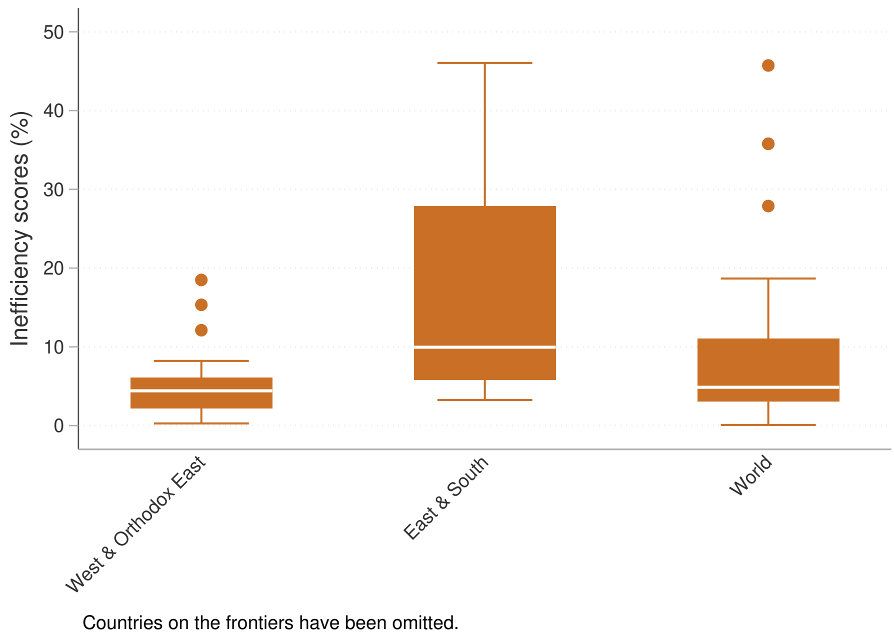
The results of cluster analysis indicate that countries can be grouped in two sets, as reported in Table 2. We could organize countries in smaller sets of more homogeneous countries than we did. We chose two work with two groups of countries, because having more groups would come at the cost of sample size. A rule of thumb for the use of DEA analysis establishes that the sample size n should be equal to or greater than $max\{m \cdot s, 3 \cdot (m+s)\}$, where m are inputs and s is output. In our case, the threshold is n = 21. Thus, we grouped countries in: Western and Orthodox Eastern ones (characterized by, on average, little genetic distance with respect to United States, and nearly 12 years of schooling), and Eastern and Southern countries (characterized by, on average, greater genetic distance with respect to the United States, and l8.5 years of schooling). The former group is made of 41 units, whereas the second includes 33 countries, for a total of 74 countries with complete information on inputs and output. More details about the cluster analysis, including a dendrogram and the list of countries selected in the two groups, are available in Table 7 and Figure 8 in Appendix A.

Table 2: Set of culturally and genetically homogeneous countries.

Variables	West & Orthodox East	East & South
Genetic distance	0.01	0.03
Reformed West	0.17	0
New West	0.15	0
Old West	0.27	0
Returned West	0.19	0
Orthodox East	0.22	0
Indic East	0	0.24
Islamic East	0	0.18
Sinic East	0	0.09
Latin America	0	0.30
Sub-Saharan Africa	0	0.18
Years of schooling	11.75	8.53
Observations	41	33

4.2 Overview of the main findings

Figure 1: Distribution of inefficiency scores by groups of countries.



Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration on data sourced from WHR 2021.

Figure 1 shows the distribution of inefficiency scores for Western and orthodox Eastern countries (henceforth, WOE), Eastern and Southern countries (henceforth, E&S), and for the whole set of countries (World). Inefficiency scores for the World group have been computed assuming a unique efficient frontier for all the countries. We regard these scores as a robustness check compared to our benchmark models that assume two separate efficient frontiers. As the box and whiskers show, the distributions of inefficiency scores between WOE and E&S are quite different: the median inefficiency score is 4.42% among WOE, and 9.95% among E&S. Also the range between the two groups is quite different: the standard deviation among WOE is 4.59%, and among E&S is 13.53%. Indeed, 90% of all inefficiency scores in the first group is comprised between 0.27% and 12%; in case of E&S the scores range from a minimum of 3.25% to 35.77% in correspondence of the 90th percentile.

Table 3 provides an overview of the results by distinguishing countries by group and returns to scale. Among WOE, the model identified 18 countries on the frontier, and 23 below the frontier. Among the efficient countries, 13 have constant returns to scale, and 5 increasing return to scale. Countries in the former group are totally efficient: they use their inputs efficiently, and they operate at an optimal scale. Countries in the second group are technically efficient, but not scale efficient: they could increase efficiency by expanding their scale to the benefit of SWB. Among the 23 inefficient countries, 1 (Croatia) faces constant returns to scale, and the remaining 22 face increasing returns to scale. These countries are all under-utilizing their inputs and, with the exception of Croatia, would benefit from expanding their scale. Among E&S, we identified 19 efficient countries: 13 facing constant returns to scale, 2 decreasing returns to scale, and 4 increasing returns to scale. The countries below the efficient frontier are 14 – among these 3 face constant returns to scale, 1 decreasing returns to scale, and 10 increasing returns to scale.

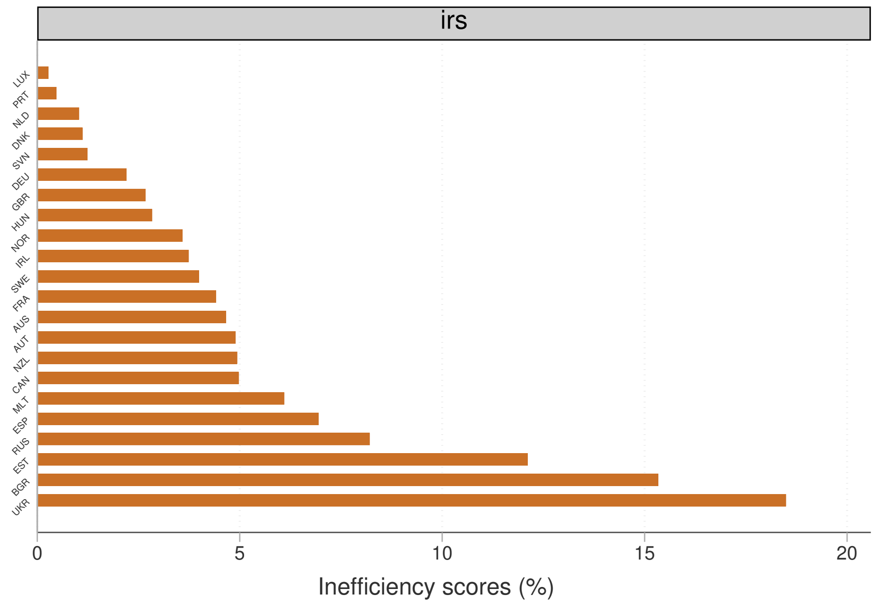
Table 3: Returns to scale and efficiency by groups of countries.

Returns to scale	West & Orthodox East	East & South	World
	Countries on the frontier		
crs	13	13	19
drs	0	2	0
irs	5	4	5
total	18	19	24
	Countries below the frontier		
crs	1	3	4
drs	0	1	4
irs	22	10	42
total	23	14	50

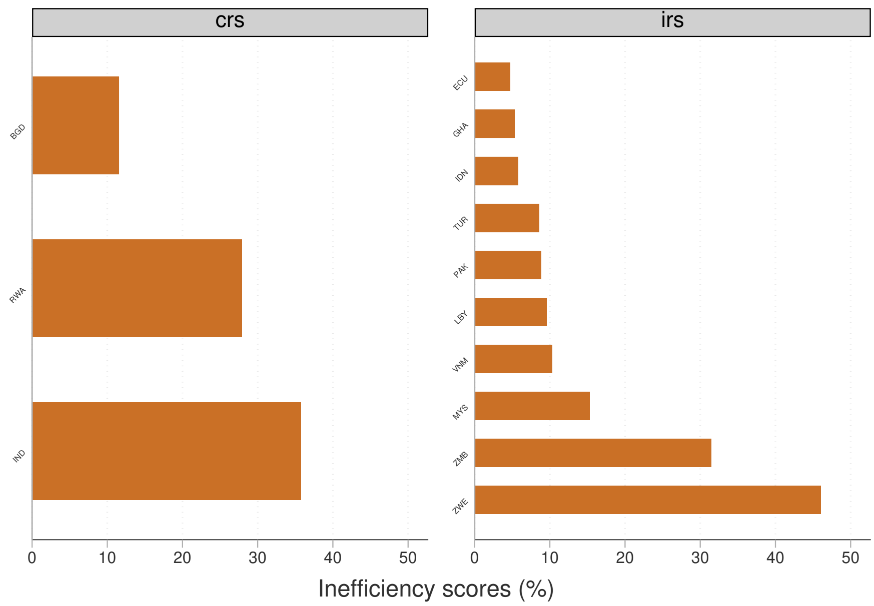
Note: the countries on the drs efficient frontier are Mexico and Uruguay. The one below the frontier is Singapore. The inefficient country under crs is Croatia.
Source: authors' own elaboration on data sourced from WHR 2021.

Figure 2 focuses on the countries below the efficient frontier, and shows

Figure 2: Inefficiency scores by returns to scale. Inefficient WOE countries have only IRS. Inefficient E&S countries face CRS and IRS.



(a) Western and Orthodox Eastern countries



(b) Eastern and Southern countries

Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration of data sourced from WHR 2021.

inefficiency scores by return to scales and groups of countries. Most WOE countries show modest inefficiency, with rates below 5%. On the contrary, most E&S countries have inefficiency scores around 10%. In other words, although both groups of countries face technical and scale inefficiencies, E&S appear further away from their frontier compared to WOE countries.

4.3 Detailed results

Tables 4 and 5 report the results for efficient and inefficient countries, respectively. In particular, for each country, the table shows the ranking (according to technical efficiency), technical efficiency (VRS), scale efficiency (SCALE), total efficiency (CSR), the nature of returns to scale (RTS), and the average scores for the output and input variables (Cantril ladder, GDP per capita, social support (x 10), healthy life expectancy at birth, freedom of choice (x 10), generosity and absence of corruption (x 10)). Scores have been multiplied by ten for comparability of scales across variables.

Table 4: List of efficient countries and respective average scores of inputs and output. The top panel refers to WOE countries; the bottom panel refers to E&S countries.

Country	*Rank*	*VRS*	*SCALE*	*CRS*	*RTS*	*Cantril ladder*	*GDP pc*	*Social support*	*HLE at birth*	*Freedom of choice*	*Generosity*	*Corruption (absence)*
						Western & Orthodox Eastern countries						
Italy	1	1	1	1	*crs*	6.45	10.66	8.38	73.8	7.09	2.07	1.34
Belgium	1	1	1	1	*crs*	6.77	10.85	8.84	72.2	7.76	1.17	3.28
Slovakia	1	1	1	1	*crs*	6.24	10.4	9.33	69.2	7.71	1.6	.74
Lithuania	1	1	1	1	*crs*	6.06	10.52	9.18	67.9	7.8	.37	2.17
Greece	1	1	1	1	*crs*	5.95	10.32	8.91	72.6	6.14	0	1.52
Finland	1	1	1	1	*crs*	7.78	10.79	9.37	72	9.48	2.37	8.05
Romania	1	1	1	1	*crs*	6.13	10.31	8.42	67.5	8.48	.67	.46
Cyprus	1	1	1	1	*crs*	6.14	10.59	7.76	73.9	7.4	2.81	1.35
Kyrgyzstan	1	1	1	1	*crs*	5.69	8.57	8.77	64.4	9.2	2.86	1.15
Israel	1	1	1	1	*crs*	7.33	10.6	9.46	73.5	8.34	3.74	2.57
United States	1	1	1	1	*crs*	6.94	11.04	9.17	68.2	8.36	4.33	2.93
Poland	12	1	1	1	*crs*	6.24	10.41	8.78	69.7	8.83	.58	3.04
Switzerland	13	1	1	1	*crs*	7.69	11.14	9.49	74.4	9.13	3.25	7.06
Latvia	14	1	0.983139	0.983139	*irs*	5.97	10.34	9.36	67.1	6.98	.95	2.11
Kazakhstan	15	1	0.969517	0.969517	*irs*	6.27	10.18	9.51	65.2	8.52	2.34	2.92
Moldova	16	1	0.966013	0.966013	*irs*	5.8	9.48	8.09	65.7	7.84	1.96	1.16
Armenia	17	1	0.906527	0.906527	*irs*	5.49	9.52	7.82	67.2	8.44	1.16	4.17
Albania	18	1	0.951194	0.951194	*irs*	5	9.54	6.86	69	7.77	1.89	.86
						Eastern & Southern countries						
Chile	1	1	1	1	*crs*	5.94	10.1	8.69	70	6.59	1.86	1.4
Brazil	1	1	1	1	*crs*	6.45	9.59	8.99	66.6	8.3	2.27	2.38
Thailand	1	1	1	1	*crs*	6.02	9.82	9.03	67.4	8.98	5.98	1.23
Philippines	1	1	1	1	*crs*	6.27	9.09	8.45	62	9.1	2.06	2.52
Morocco	1	1	1	1	*crs*	5.06	8.92	5.35	66.2	7.57	.44	2.43
Argentina	1	1	1	1	*crs*	6.09	10	8.96	69	8.17	.78	1.7
Colombia	1	1	1	1	*crs*	6.35	9.6	8.73	68	8.22	1.17	1.46
Algeria	1	1	1	1	*crs*	4.74	9.34	8.03	66.1	3.85	2.94	2.59
El Salvador	1	1	1	1	*crs*	6.45	9.08	7.64	66.4	8.77	1.8	3.18
South Korea	1	1	1	1	*crs*	5.9	10.66	7.83	73.9	7.06	2.33	2.82
Japan	1	1	1	1	*crs*	5.91	10.63	8.78	75.1	8.06	.34	3.83
Peru	1	1	1	1	*crs*	6	9.46	8.09	68.4	8.15	1.59	1.26
Guatemala	1	1	1	1	*crs*	6.26	9.06	7.74	65.1	9.01	2.26	2.27
Uruguay	1	1	0.984002	0.984002	*drs*	6.6	9.98	9.33	69.1	9.03	1.93	4.01
Mexico	15	1	0.995109	0.995109	*drs*	6.43	9.89	8.52	68.6	9.03	1.48	1.91
Mali	16	1	0.994061	0.994061	*irs*	4.99	7.75	7.55	52.2	6.7	2.51	1.54
South Africa	17	1	0.914385	0.914385	*irs*	5.03	9.43	8.48	56.9	7.38	1.55	1.8
Uganda	18	1	0.944835	0.944835	*irs*	4.95	7.69	8.05	56.1	7.04	4.27	1.74
Tunisia	19	1	0.958389	0.958389	*irs*	4.32	9.28	6.1	67.2	6.59	.8	1.11

Source: authors' own elaboration of data sourced from WHR 2021.

Countries with VRS, SCALE and CRS efficiency scores equal to one are located on the frontier, and therefore are considered as 100% efficient. Countries with scores smaller than one are located below the frontier, and are regarded as inefficient. The scores indicate how close to the frontier they are. In the first table we have 37 efficient countries of which 18 belong to the group of WOE, and 19 belong to the second group. The majority of these countries have efficiency scores (VRS, SCALE, and CRS) equal to 1. These countries lie on the frontier, and they are those who reach the highest Cantril ladder score given their inputs. Some countries in Table 4 are technically efficient (VRS = 1), but they are not scale efficient (SCALE < 1). This group comprises Latvia, Kazakhstan, Moldova, Armenia and Albania among WOE, and Uruguay, Mexico, Mali, South Africa, Uganda and Tunisia among E&S. These countries use their inputs efficiently, but their scale is inefficient. Figure 3 shows the size of scale inefficiencies for the countries on the frontier, but operating under increasing returns to scale (RTS = irs). Armenia and South Africa have the largest scale inefficiencies (9.3% and 8.6%, respectively) followed by Uganda, Albania, and Tunisia. These countries would benefit from expanding their inputs, as 1% increase in output requires a change of less than 1% in inputs.

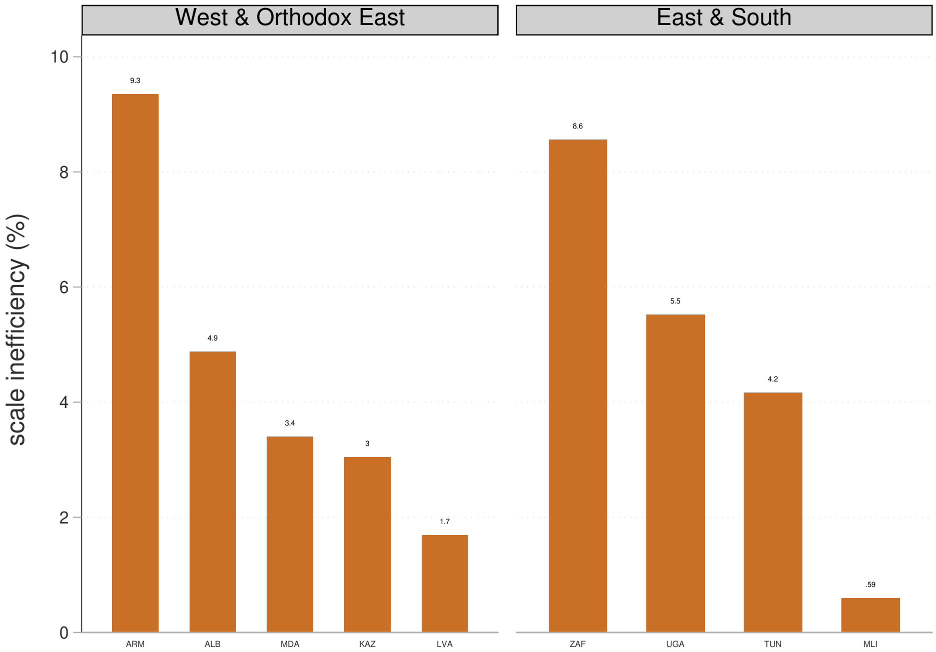
Countries located on the frontier but operating under decreasing returns to scale (RTS = drs), are also technically efficient in using their inputs, but a variation in output of 1% would require a variation in input of more than 1%. These countries pose an interpretative challenge, as they should decrease their scale to improve efficiency. Among efficient countries, only Uruguay and Mexico face decreasing returns to scale.

Table 5 lists the inefficient countries in increasing order of inefficiency. Luxembourg, Portugal and Netherlands top the ranking of the least inefficient countries, with technical efficiency scores of about 99%, whereas Estonia, Bulgaria and Ukraine close the ranking with technical efficiency scores below 87%. All these countries, except Croatia, face increasing returns to scale. In other words they face two sources of inefficiency: technical inefficiency (which, for what concerns WOE, is comprised between 0.3% and 18.5%), and scale inefficiency, which ranges from 0.3% for Luxembourg to 20.8% for Ukraine.

With technical inefficiencies of about 5%, Singapore, Ecuadaor and Ghana top the ranking of the least inefficient countries in the E&S group. At the bottom of the ranking are Zambia, India and Zimbabwe, with efficiency scores below 68.5%.

In total, 4 countries, among the inefficient ones, face constant return to scale (Croatia, Bangladesh, India, and Rwanda). This indicates that they do not suffer any scale inefficiency. Thus, given the resources available, they should be able to achieve higher SWB. The analysis of slacks, measures indicating how much a country can improve its efficiency without worsening any other input or output, reveals that these countries could increase their efficiency mostly by investing in health care, to expand the number of healthy life years a new born can expect, and improving individual freedom of choice.

Figure 3: Scale inefficiencies for countries on the frontier and facing increasing returns to scale.



Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration of data sourced from WHR 2021.

Table 5: List of inefficient countries and respective average scores of inputs and output.

Country	*Rank*	*VRS*	*SCALE*	*CRS*	*RTS*	*Cantril ladder*	*GDP pc*	*Social support*	*HLE at birth*	*Freedom of choice*	*Generosity*	*Corruption (absence)*
						Western & Orthodox Eastern countries						
Luxembourg	19	0.997249	0.997088	0.999839	*irs*	7.4	11.65	9.12	72.6	9.3	2.44	6.1
Portugal	20	0.995265	0.983436	0.988115	*irs*	6.1	10.46	8.76	72.6	8.82	.55	.85
Netherlands	21	0.989663	0.988150	0.998471	*irs*	7.43	10.95	9.41	72.4	8.86	5.01	6.4
Denmark	22	0.988774	0.979253	0.990371	*irs*	7.69	10.95	9.58	72.7	9.63	3.09	8.26
Slovenia	23	0.987594	0.981924	0.994259	*irs*	6.67	10.56	9.49	71.4	9.45	1.87	2.15
Germany	24	0.977962	0.976912	0.998926	*irs*	7.04	10.89	8.86	72.5	8.85	3.46	5.38
United Kingdom	25	0.973245	0.970586	0.997268	*irs*	7.16	10.75	9.43	72.5	8.54	5.59	5.15
Hungary	26	0.971613	0.967109	0.995364	*irs*	6	10.39	9.47	68	7.98	.94	1.16
Norway	27	0.964169	0.959691	0.995356	*irs*	7.44	11.06	9.42	73.3	9.54	3.99	7.29
Ireland	28	0.962582	0.961432	0.998806	*irs*	7.25	11.37	9.44	72.4	8.92	3.62	6.27
Sweden	29	0.960043	0.959064	0.998980	*irs*	7.4	10.88	9.34	72.7	9.42	3.8	7.5
France	30	0.955824	0.951296	0.995263	*irs*	6.69	10.74	9.58	74	8.27	1.56	4.32
Australia	31	0.953356	0.950697	0.997212	*irs*	7.23	10.81	9.43	73.9	9.18	4.09	5.7
Austria	32	0.951024	0.943272	0.991848	*irs*	7.2	10.94	9.64	73.3	9.03	3.48	5.43
New Zealand	33	0.950591	0.946720	0.995927	*irs*	7.21	10.67	9.39	73.4	9.12	4.45	7.66
Canada	34	0.950211	0.949065	0.998794	*irs*	7.11	10.8	9.25	73.8	9.12	4	5.64
Croatia	35	0.948669	0.948669	1	*crs*	5.63	10.26	9.36	70.8	7.39	1.51	.68
Malta	36	0.938981	0.934017	0.994714	*irs*	6.73	10.68	9.22	72.2	9.24	3.76	3.11
Spain	37	0.930554	0.926253	0.995378	*irs*	6.46	10.62	9.49	74.7	7.78	2.4	2.7
Russia	38	0.917874	0.904230	0.985135	*irs*	5.44	10.21	9.1	64.7	7.15	1.73	1.52
Estonia	39	0.878890	0.872057	0.992226	*irs*	6.03	10.51	9.34	68.8	8.87	1.93	4.24
Bulgaria	40	0.846612	0.846471	0.999833	*irs*	5.11	10.05	9.48	67	8.22	1.8	.57
Ukraine	41	0.815066	0.792420	0.972217	*irs*	4.7	9.46	8.83	64.9	7.15	2.08	1.15
						Eastern & Southern countries						
Singapore	20	0.967448	0.879313	0.908900	*drs*	6.38	11.49	9.25	77.1	9.38	3.16	9.3
Ecuador	21	0.952557	0.950272	0.997601	*irs*	5.81	9.34	8.08	68.8	8.3	1.74	1.61
Ghana	22	0.946841	0.910394	0.961507	*irs*	4.97	8.6	7.46	57.6	7.87	4.05	1.43
Indonesia	23	0.941946	0.915696	0.972132	*irs*	5.35	9.38	8.02	62.3	8.66	8.44	1.39
Turkey	24	0.914076	0.888722	0.972262	*irs*	4.87	10.25	7.92	67.2	6.31	1.53	2.4
Pakistan	25	0.911745	0.870417	0.954671	*irs*	4.44	8.45	6.17	58.9	6.85	4.12	2.24
Libya	26	0.904049	0.893348	0.988163	*irs*	5.33	9.63	8.27	62.3	7.62	2.16	3.14
Vietnam	27	0.896887	0.889112	0.991331	*irs*	5.47	8.99	8.48	68.1	9.52	1.63	2.12
Bangladesh	28	0.884288	0.884288	1	*crs*	5.11	8.47	6.73	64.8	9.02	2.37	3.44
Malaysia	29	0.846884	0.837068	0.988410	*irs*	5.43	10.25	8.42	67.2	9.16	4.12	2.18
Rwanda	30	0.721235	0.721235	1	*crs*	3.27	7.71	4.89	61.7	8.69	3.53	8.32
Zambia	31	0.685290	0.648966	0.946994	*irs*	3.31	8.15	6.38	55.8	8.11	3.66	1.68
India	32	0.642274	0.642274	1	*crs*	3.25	8.82	5.61	60.5	8.76	4	2.48
Zimbabwe	33	0.539528	0.525510	0.974018	*irs*	2.69	7.95	7.59	56.2	6.32	2.25	1.69

Source: authors' own elaboration of data sourced from WHR 2021.

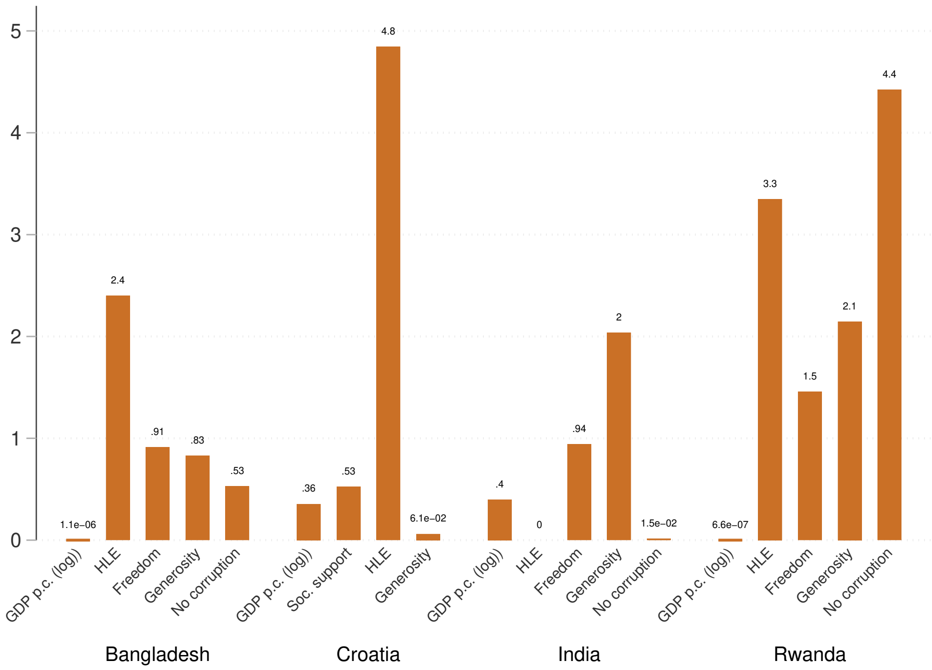
In case of Rwanda reducing corruption would play a major role along with healthy life years (see Figure 4).

Except Singapore, who faces decreasing returns to scale, the 32 remaining inefficient countries face increasing returns to scale. These countries suffer technical inefficiencies due to poor management, and scale inefficiencies. Figure 5 shows the difference between scale and technical (or pure) inefficiency for each country. All the countries, except Portugal, have scale inefficiencies smaller than technical inefficiencies. This means that these countries are away from the efficient frontier, and this is because of their poor technical efficiency. As the latter relates to the ability to transform inputs into output, it signals poor management of resources. The average difference between scale and technical inefficiency is -4.62% among WOE, and -12% among E&S.

4.4 The correlates of well-being efficiency

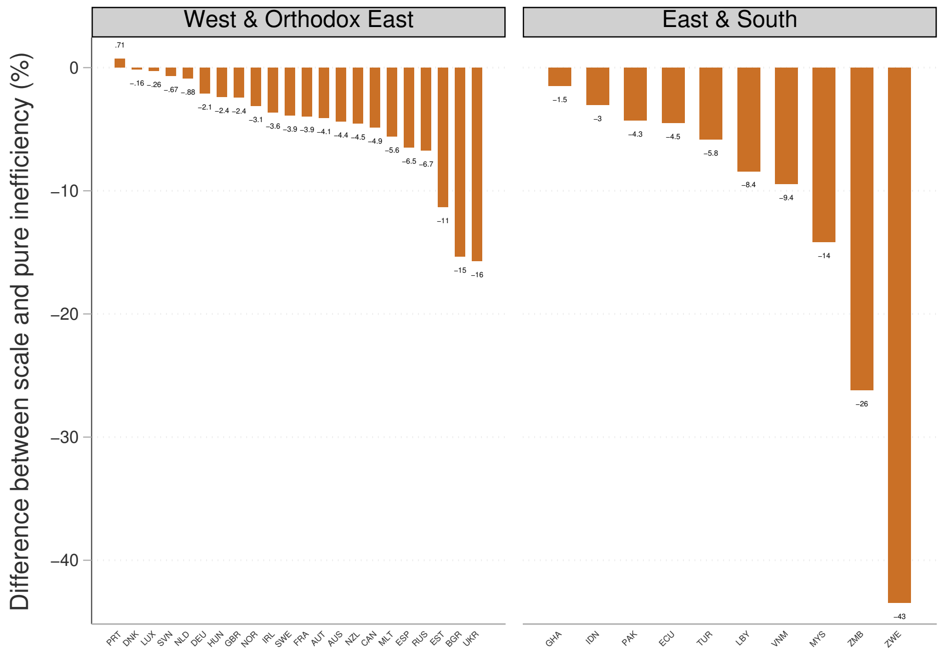
Previous section presented a measure of well-being efficiency derived from the framework of WHRs. The scores provide a ranking of countries based on their ability to transform inputs into output. Moreover, it is possible to distinguish various sources of inefficiency, and to put this information in relation to return to scales. The combined interpretation of the results provides insights about the sources of inefficiency and indicates some venues for improving SWB. In the remainder of this section, we focus on the correlates of inefficiency

Figure 4: Possibilities to improve well-being efficiencies in a selected group of countries.



Note: scores are in the same units of the input variables.
Source: authors' own elaboration of data sourced from WHR 2021.

Figure 5: Comparison of scale and technical inefficiency for countries below the frontier and facing increasing returns to scale.



Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration of data sourced from WHR 2021.

scores. Table 6 reports the correlation matrices of inefficiency scores and the variables from WHRs for WOE (top panel) and E&S (bottom panel), respectively.

Table 6: Correlation table of inefficiency scores with inputs and output. Sample of Western and Orthodox Eastern countries.

	Inefficiency scores (%)	Cantril ladder	GDP per capita PPP US$ 2011	Social support (x 10)	Healthy life expectancy at birth	Freedom of choice (x 10)	Generosity (x 10)	Absence of corruption (x 10)
					Western and Orthodox Eastern countries			
Inefficiency scores (%)	1							
Cantril ladder	-0.749***	1						
GDP per capita PPP US$ 2011	-0.733***	0.891***	1					
Social support (x 10)	-0.150	0.359*	0.285	1				
Healthy life expectancy at birth	-0.672***	0.821***	0.723***	0.322	1			
Freedom of choice (x 10)	-0.554**	0.816***	0.717***	0.235	0.646***	1		
Generosity (x 10)	-0.240	0.686***	0.469*	0.233	0.477*	0.477*	1	
Absence of corruption (x 10)	-0.443*	0.888***	0.749***	0.303	0.617**	0.722***	0.741***	1
Observations	23							
					Eastern and Southern countries			
Inefficiency scores (%)	1							
Cantril ladder	-0.915***	1						
GDP per capita PPP US$ 2011	-0.582*	0.758**	1					
Social support (x 10)	-0.540*	0.758**	0.762**	1				
Healthy life expectancy at birth	-0.580*	0.776**	0.819***	0.617*	1			
Freedom of choice (x 10)	-0.227	0.409	0.234	0.119	0.496*	1		
Generosity (x 10)	-0.0735	-0.0188	-0.0319	-0.131	-0.246	0.202	1	
Absence of corruption (x 10)	-0.0583	0.117	0.275	-0.0745	0.503*	0.360	-0.101	1
Observations	14							

Note: countries on the frontier have been omitted. * $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$

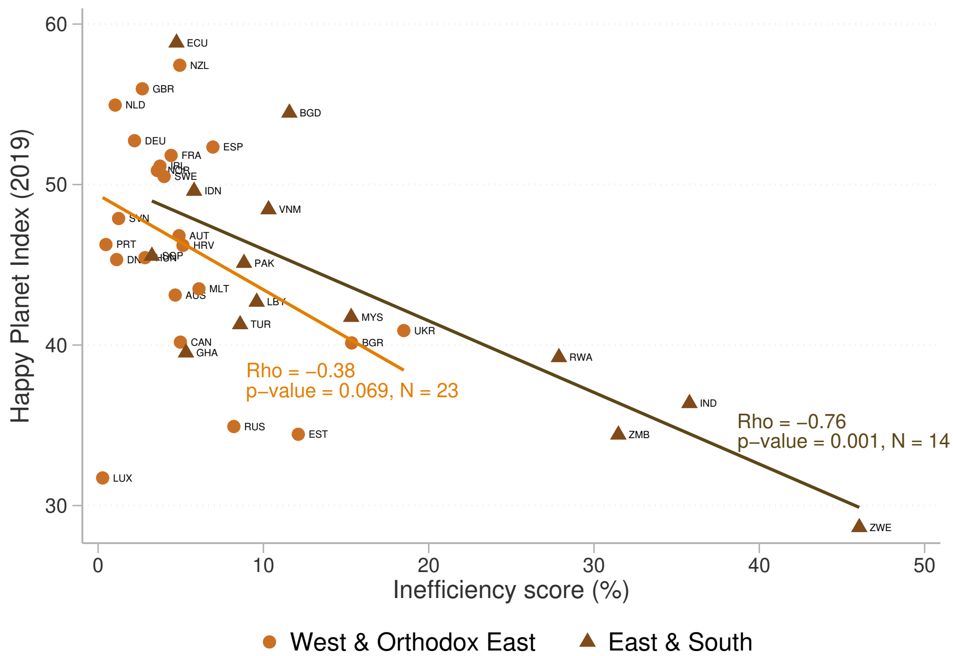
Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration of data sourced from WHR 2021.

Coefficients indicate that the Cantril ladder, GDP per capita, and healthy life expectancy correlate negatively and significantly with inefficiency scores. The magnitude of coefficients changes between the two groups of countries, with the Cantril ladder correlating to a larger degree among E&S than among WOE. Generosity, on the contrary, never significantly correlates with inefficiency scores. Less corruption and more freedom of choice also significantly and negatively correlate with inefficiency scores, but only among WOE. Among E&S the absence of corruption, freedom of choice and social support are not statistically associated to inefficiency.

The second column of Table 6 also shows the correlates of Cantril ladder, thus providing a hint of the relationships underlying the WHRs. Unsurprisingly, we find that all the variables correlates significantly and with the right sign with our measure of SWB. However, freedom of choice, generosity and absence of corruption lose significance in the group of E&S.

In the last part of our analysis we investigate the relationship between our measure of well-being efficiency and two other measures: the Happy Planet Index (HPI), which provides a country-level measure of sustainable well-being, and a traditional measure of economic efficiency. Data on the Happy Planet Index (Happy Planet Index, 2021) are freely available online.[1] In extreme synthesis, the HPI equals life expectancy multiplied by Cantril ladder, divided by the ecological footprint. According to the authors, the HPI can be regarded as a measure of efficiency in itself as the numerator is a measure of output, and the denominator includes the inputs provided by the natural environment. This is why it is regarded as a measure of sustainable well-being.

Figure 6: Correlation between inefficiency scores and the Happy Planet Index. Sustainable well-being, as defined by the HPI, correlates negatively with well-being inefficiency.



Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration of data sourced from WHR 2021 and HPI 2021.

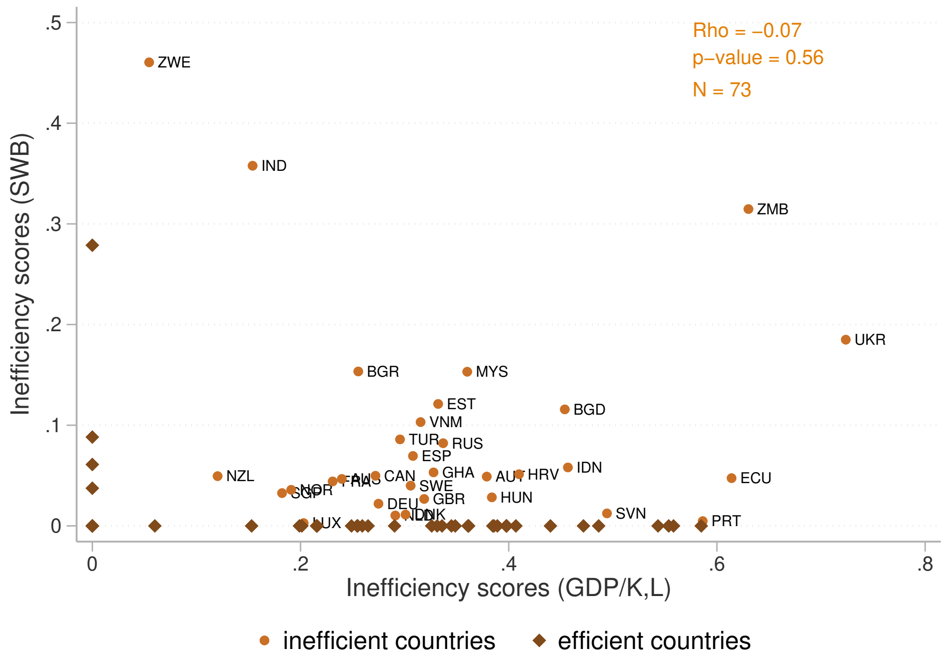
Figure 6 shows the within groups correlation between our measure of

[1]Please, visit the website: `https://happyplanetindex.org/hpi/`.

well-being inefficiency (on the x axis) and the HPI (on the y axis). Higher inefficiency scores correlate negatively and significantly with the HPI in both groups of countries, although the correlation is stronger and more significant among E&S countries. These results suggest that well-being efficiency correlates meaningfully with a third party variable of sustainable well-being. This result, however, may be driven by the fact that both measures use the same variable (Cantril ladder) as an output. We emphasize that the two measures of SWB are not exactly the same: the WHR measure averages the within-country Cantril ladder scores from 2017 to 2019. The HPI uses only the data from 2019. However, to test the robustness of our finding, we run a simple OLS regression of well-being inefficiency on the Cantril ladder and the HPI. Results confirm the association between our measure of efficiency and the HPI (regression results are available in Table 9 in Appendix C).

Next we compare our measure of efficiency with a traditional measure of economic efficiency. As we did not find international data on economic efficiency for our sample of countries, we computed economic efficiency by applying DEA to measures of input and output issued from the Penn World Tables v. 10 (Feenstra et al., 2015). We use Real GDP at constant 2017 national prices (in mil. 2017US$) as a measure of output; capital stock at constant 2017 national prices (in mil. 2017US$), and number of persons engaged (in millions) as measures of inputs. Figure 7 shows the correlation between this economic measure of efficiency and our measure of well-being efficiency. Except for five countries that appear efficient with both variables (the countries are: Armenia, Kazakhstan, Mali, Poland and United States), the observations from the two set of variables are not statistically associated. To investigate this aspect further, we run a Spearman rank test of equality of ranking. The null hypothesis is that the rankings resulting from the two measures of inefficiency are independent. The Spearman's coefficient is -0.04, with a p-value = 0.73 and 73 observations. This result suggests that the two variables are independent: well-being efficient countries are not economic efficient countries, that is the countries that are better equipped to transform their resources in well-being are not the same that are better equipped in transforming capital and labor into GDP. This result is consistent with the view that the quality of growth matters for well-being (Helliwell, 2016), and that a performing economy is not necessarily a mean to better lives.

Figure 7: Correlation between well-being and economic inefficiency scores.



Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration of data sourced from WHR 2021 and PWT v.10.

5 Conclusion

Numerous studies make the case for subjective well-being (SWB) – a single measure summarizing the many economic and non-economic aspects of what makes a life worth living – as a measure of economic and social development (Fleurbaey, 2009; OECD, 2013; Easterlin, 2019). The aim of our work is to provide a measure of well-being efficiency that goes beyond income. We propose to assess countries' productivity of SWB using non-parametric techniques, the determinants identified in the series of World Happiness Reports (WHRs) as inputs, and SWB as a measure of output. The WHRs demonstrate that six factors (real GDP per capita, healthy life expectancy, social support, freedom of choice, absence of corruption, and generosity) explain about three-quarters of the variation in SWB around the world (Helliwell et al., 2013).

We believe that a measure of well-being efficiency has significant advantages over traditional productivity measures. For instance, our scores indicate countries' ability to transform inputs into SWB – a valid and reliable measure of how people fare with their lives as a whole. Moreover, the idea that SWB can be produced more or less efficiently – and that this efficiency can be measured – is fairly recent in the literature. Additionally, current SWB policy advice generally discusses the amount of inputs, not how well they are used. Perhaps the Nordic countries, who generally rank among the countries in the world with the highest SWB, do so because they have the greatest amount of inputs, but are these inputs used efficiently? We believe that identifying under-performing countries and leading examples can provide useful information to policy makers.

Our results indicate that it is possible to derive a measure of well-being efficiency using the framework of WHRs. The scores provide a ranking of countries based on their ability to transform inputs into output. For instance, countries with greater productive capacity and better health are better able to exploit their inputs. This finding implies policy makers might want to invest in better health not only for the direct benefits it brings for SWB, but also for the indirect effects that result from a more efficient use of inputs. Moreover, it is possible to distinguish various components of total efficiency, and to put this information in relation to return to scales. The combined interpretation of our results provides insights about the sources of inefficiency and indicates some venues for improvement.

The correlation of our measure of well-being efficiency with third party measures of sustainable well-being, and economic efficiency provides interesting insights for modern societies. We found that countries' efficiency in transforming inputs into SWB correlates positively and significantly with the

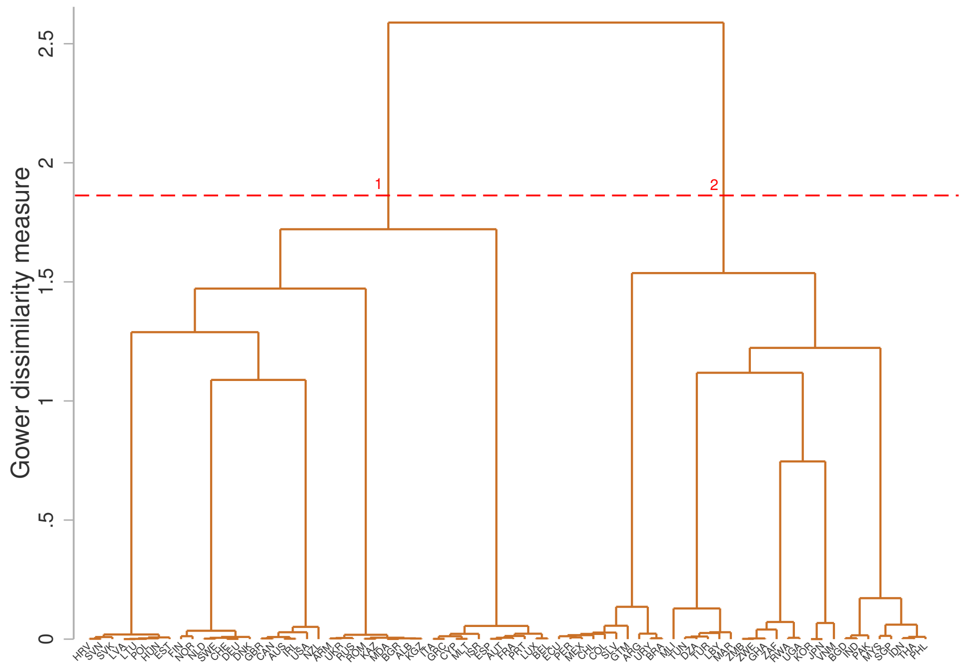
Happy Planet Index, but it is unrelated to a common measure of economic efficiency. This result indicates that economic and well-being efficiency are not necessarily associated. We only found 5 countries out of 73 in which the two indices correlate. In other words, the countries that are better at transforming their inputs into SWB are not the same that are more effective at turning capital and labor into GDP. We consider this result as further evidence that the quality of economic growth matters for SWB (Helliwell, 2016).

Two aspects are worth emphasizing. The first, is that countries on the frontier are efficient. This does not imply, however, that they can not improve their SWB. The second, is that high efficiency does not imply high SWB: a country characterized by low levels of SWB may still use its inputs efficiently.

We regard present work as a proof-of-concept as we are aware of various limits that we will try to overcome in coming months. For instance, we believe that the idea of running separate analysis for groups of homogeneous countries is valid. However, data availability limited our possibilities to refine the composition of the two groups we identified. In particular, lack of data on culture halved our sample. We plan to retrieve the missing information or to resort to different variables to increase as much as possible the sample of countries available for present analysis. This will also allow us to improve the internal consistency of our groups of countries. Another problem has to do with the interpretation of efficiency for countries facing decreasing returns to scale. As discussed earlier, the implications for these countries is to reduce their scale to improve their efficiency. This does not seem a desirable policy if the aim is to improve SWB. Another limitation has to do with causality. Although we adopted a well-established framework, we can not disregard the evidence suggesting that SWB contributes to many of the variables we include among the inputs. For instance, happier people live longer and healthier lives. In a possible extension of our model, we should explore the possibility to include a measure of SWB/positive affect among the inputs. Finally, we wish to take full advantage of the panel data made available by WHRs, and produce Malmquist indices of well-being efficiency.

A Dendrogram and list of countries by groups.

Figure 8: Dendrogram showing the groups formed applying cluster analysis to genetic distance and cultural similarity.



Source: authors' own elaboration on data sourced from Welzel (2013), Barro et al. (2021), Spolaore and Wacziarg (2018).

Table 7: List of countries belonging to the two groups identified with cluster analysis.

West & Orthodox East		East & South	
Albania	Latvia	Algeria	Philippines
Armenia	Lithuania	Argentina	Rwanda
Australia	Luxembourg	Bangladesh	Singapore
Austria	Malta	Brazil	South Africa
Belgium	Moldova	Chile	South Korea
Bulgaria	Netherlands	Colombia	Thailand
Canada	New Zealand	Ecuador	Tunisia
Croatia	Norway	El Salvador	Turkey
Cyprus	Poland	Ghana	Uganda
Denmark	Portugal	Guatemala	Uruguay
Estonia	Romania	India	Vietnam
Finland	Russia	Indonesia	Zambia
France	Slovakia	Japan	Zimbabwe
Germany	Slovenia	Libya	
Greece	Spain	Malaysia	
Hungary	Sweden	Mali	
Ireland	Switzerland	Mexico	
Israel	Ukraine	Morocco	
Italy	United Kingdom	Pakistan	
Kazakhstan	United States	Peru	
Kyrgyzstan			

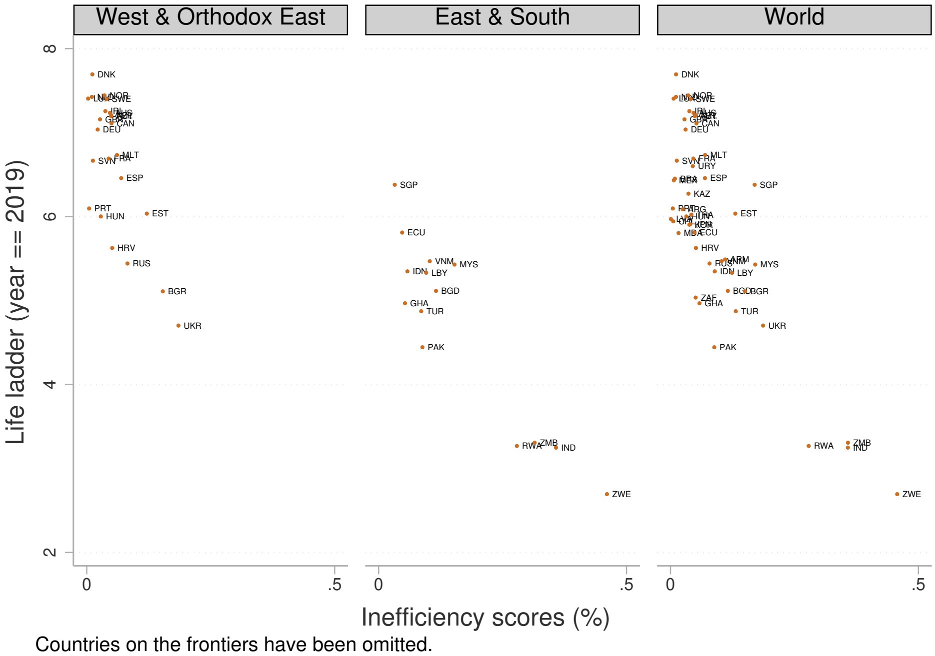
B Efficiency scores and average inputs and output for the whole sample.

Table 8: Results for the whole World.

Country	*Rank*	*VRS*	*SCALE*	*CRS*	*RTS*	*Cantril ladder*	*GDP pc*	*Social support*	*HLE at birth*	*Freedom of choice*	*Generosity*	*Corruption (absence)*
Cyprus	1	1	1	1	*crs*	6.14	10.59	7.76	73.9	7.4	2.81	1.35
Finland	1	1	1	1	*crs*	7.78	10.79	9.37	72	9.48	2.37	8.05
Guatemala	1	1	1	1	*crs*	6.26	9.06	7.74	65.1	9.01	2.26	2.27
El Salvador	1	1	1	1	*crs*	6.45	9.08	7.64	66.4	8.77	1.8	3.18
Lithuania	1	1	1	1	*crs*	6.06	10.52	9.18	67.9	7.8	.37	2.17
Algeria	1	1	1	1	*crs*	4.74	9.34	8.03	66.1	3.85	2.94	2.59
Colombia	1	1	1	1	*crs*	6.35	9.6	8.73	68	8.22	1.17	1.46
Greece	1	1	1	1	*crs*	5.95	10.32	8.91	72.6	6.14	0	1.52
Philippines	1	1	1	1	*crs*	6.27	9.09	8.45	62	9.1	2.06	2.52
Slovakia	1	1	1	1	*crs*	6.24	10.4	9.33	69.2	7.71	1.6	.74
Belgium	1	1	1	1	*crs*	6.77	10.85	8.84	72.2	7.76	1.17	3.28
Italy	1	1	1	1	*crs*	6.45	10.66	8.38	73.8	7.09	2.07	1.34
Morocco	1	1	1	1	*crs*	5.06	8.92	5.35	66.2	7.57	.44	2.43
Romania	1	1	1	1	*crs*	6.13	10.31	8.42	67.5	8.48	.67	.46
Kyrgyzstan	1	1	1	1	*crs*	5.69	8.57	8.77	64.4	9.2	2.86	1.15
Israel	1	1	1	1	*crs*	7.33	10.6	9.46	73.5	8.34	3.74	2.57
Poland	17	1	1	1	*crs*	6.24	10.41	8.78	69.7	8.83	.58	3.04
Switzerland	18	1	1	1	*crs*	7.69	11.14	9.49	74.4	9.13	3.25	7.06
United States	19	1	1	1	*crs*	6.94	11.04	9.17	68.2	8.36	4.33	2.93
Mali	20	1	0.975123	0.975123	*irs*	4.99	7.75	7.55	52.2	6.7	2.51	1.54
Peru	21	1	0.989475	0.989475	*irs*	6	9.46	8.09	68.4	8.15	1.59	1.26
Uganda	22	1	0.936127	0.936127	*irs*	4.95	7.69	8.05	56.1	7.04	4.27	1.74
Albania	23	1	0.949678	0.949678	*irs*	5	9.54	6.86	69	7.77	1.89	.86
Tunisia	24	1	0.890649	0.890649	*irs*	4.32	9.28	6.1	67.2	6.59	.8	1.11
Latvia	25	0.999177	0.982888	0.983698	*irs*	5.97	10.34	9.36	67.1	6.98	.95	2.11
Portugal	26	0.995265	0.978751	0.983407	*irs*	6.1	10.46	8.76	72.6	8.82	.55	.85
Chile	27	0.994493	0.979178	0.984601	*irs*	5.94	10.1	8.69	70	6.59	1.86	1.4
Luxembourg	28	0.993601	0.984201	0.990539	*drs*	7.4	11.65	9.12	72.6	9.3	2.44	6.1
Mexico	29	0.993231	0.987002	0.993729	*drs*	6.43	9.89	8.52	68.6	9.03	1.48	1.91
Brazil	30	0.991057	0.985569	0.994462	*irs*	6.45	9.59	8.99	66.6	8.3	2.27	2.38
Netherlands	31	0.988856	0.988150	0.999286	*irs*	7.43	10.95	9.41	72.4	8.86	5.01	6.4
Denmark	32	0.988774	0.979253	0.990371	*irs*	7.69	10.95	9.58	72.7	9.63	3.09	8.26
Slovenia	33	0.987245	0.961102	0.973520	*drs*	6.67	10.56	9.49	71.4	9.45	1.87	2.15
Moldova	34	0.983683	0.964110	0.980103	*irs*	5.8	9.48	8.09	65.7	7.84	1.96	1.16
Argentina	35	0.975248	0.974783	0.999523	*irs*	6.09	10	8.96	69	8.17	.78	1.7
United Kingdom	36	0.971826	0.970586	0.998724	*irs*	7.16	10.75	9.43	72.5	8.54	5.59	5.15
Germany	37	0.969538	0.968371	0.998796	*drs*	7.04	10.89	8.86	72.5	8.85	3.46	5.38
Hungary	38	0.968105	0.966583	0.998428	*irs*	6	10.39	9.47	68	7.98	.94	1.16
Norway	39	0.964169	0.955379	0.990884	*irs*	7.44	11.06	9.42	73.3	9.54	3.99	7.29
Kazakhstan	40	0.963840	0.958987	0.994965	*irs*	6.27	10.18	9.51	65.2	8.52	2.34	2.92
Ireland	41	0.961969	0.961432	0.999442	*irs*	7.25	11.37	9.44	72.4	8.92	3.62	6.27
South Korea	42	0.961920	0.955567	0.993396	*irs*	5.9	10.66	7.83	73.9	7.06	2.33	2.82
Japan	43	0.960317	0.938993	0.977795	*irs*	5.91	10.63	8.78	75.1	8.06	.34	3.83
Sweden	44	0.959330	0.957150	0.997728	*irs*	7.4	10.88	9.34	72.7	9.42	3.8	7.5
Thailand	45	0.957903	0.956489	0.998523	*irs*	6.02	9.82	9.03	67.4	8.98	5.98	1.23
Uruguay	46	0.955055	0.952400	0.997220	*irs*	6.6	9.98	9.33	69.1	9.03	1.93	4.01
France	47	0.953939	0.943019	0.988553	*irs*	6.69	10.74	9.58	74	8.27	1.56	4.32
Australia	48	0.953356	0.946246	0.992542	*irs*	7.23	10.81	9.43	73.9	9.18	4.09	5.7
Ecuador	49	0.951624	0.943224	0.991173	*irs*	5.81	9.34	8.08	68.8	8.3	1.74	1.61
Austria	50	0.951024	0.943272	0.991848	*irs*	7.2	10.94	9.64	73.3	9.03	3.48	5.43
South Africa	51	0.949265	0.910225	0.958873	*irs*	5.03	9.43	8.48	56.9	7.38	1.55	1.8
Croatia	52	0.948669	0.948669	1	*crs*	5.63	10.26	9.36	70.8	7.39	1.51	.68
New Zealand	53	0.948507	0.946720	0.998115	*irs*	7.21	10.67	9.39	73.4	9.12	4.45	7.66
Canada	54	0.947719	0.942227	0.994205	*irs*	7.11	10.8	9.25	73.8	9.12	4	5.64
Ghana	55	0.941521	0.893108	0.948580	*irs*	4.97	8.6	7.46	57.6	7.87	4.05	1.43
Spain	56	0.930554	0.926036	0.995145	*irs*	6.46	10.62	9.49	74.7	7.78	2.4	2.7
Malta	57	0.930210	0.930004	0.999779	*irs*	6.73	10.68	9.22	72.2	9.24	3.76	3.11
Russia	58	0.921241	0.904193	0.981495	*irs*	5.44	10.21	9.1	64.7	7.15	1.73	1.52
Pakistan	59	0.911745	0.850896	0.933261	*irs*	4.44	8.45	6.17	58.9	6.85	4.12	2.24
Indonesia	60	0.910701	0.896329	0.984219	*irs*	5.35	9.38	8.02	62.3	8.66	8.44	1.39
Vietnam	61	0.896887	0.889112	0.991331	*irs*	5.47	8.99	8.48	68.1	9.52	1.63	2.12
Armenia	62	0.889749	0.884305	0.993882	*irs*	5.49	9.52	7.82	67.2	8.44	1.16	4.17
Bangladesh	63	0.884288	0.884288	1	*crs*	5.11	8.47	6.73	64.8	9.02	2.37	3.44
Libya	64	0.876192	0.856416	0.977429	*irs*	5.33	9.63	8.27	62.3	7.62	2.16	3.14
Estonia	65	0.869371	0.869363	0.999991	*irs*	6.03	10.51	9.34	68.8	8.87	1.93	4.24
Turkey	66	0.868296	0.835021	0.961678	*irs*	4.87	10.25	7.92	67.2	6.31	1.53	2.4
Bulgaria	67	0.849562	0.845319	0.995005	*irs*	5.11	10.05	9.48	67	8.22	1.8	.57
Singapore	68	0.830180	0.829935	0.999706	*irs*	6.38	11.49	9.25	77.1	9.38	3.16	9.3
Malaysia	69	0.829205	0.825303	0.995295	*irs*	5.43	10.25	8.42	67.2	9.16	4.12	2.18
Ukraine	70	0.813287	0.792262	0.974149	*irs*	4.7	9.46	8.83	64.9	7.15	2.08	1.15
Rwanda	71	0.721235	0.721235	1	*crs*	3.27	7.71	4.89	61.7	8.69	3.53	8.32
India	72	0.642274	0.642191	0.999870	*irs*	3.25	8.82	5.61	60.5	8.76	4	2.48
Zambia	73	0.642116	0.642116	1	*crs*	3.31	8.15	6.38	55.8	8.11	3.66	1.68
Zimbabwe	74	0.542737	0.499658	0.920626	*irs*	2.69	7.95	7.59	56.2	6.32	2.25	1.69

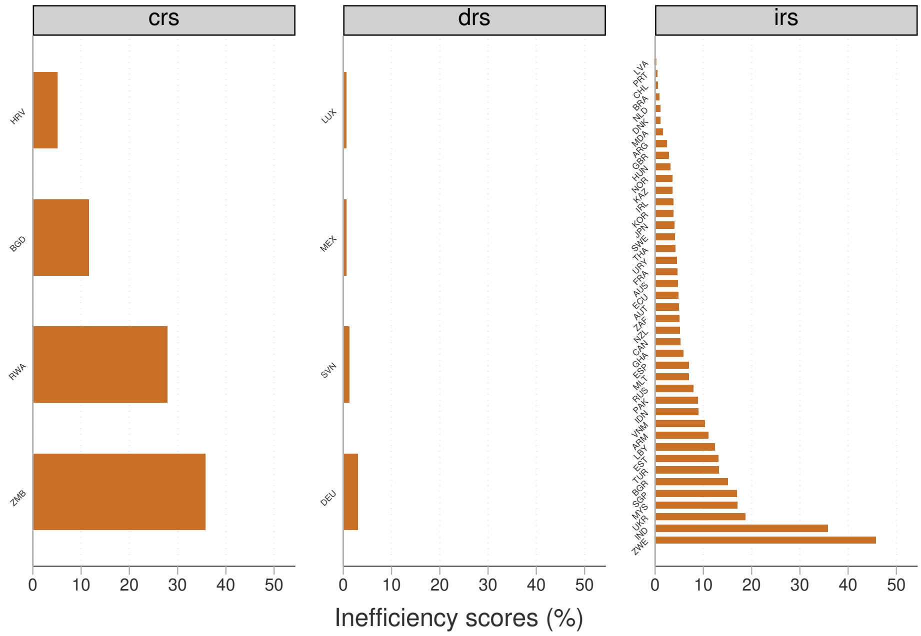
Source: authors' own elaboration of data sourced from WHR 2019.

Figure 9: Correlation between inefficiency scores and life ladder by groups of countries. Note that the scores do not change much when they are computed by groups of countries or for the whole world.



Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration of data sourced from WHR 2021.

Figure 10: Inefficiency scores by returns to scale for the whole world.



Note: the chart shows inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency.
Source: authors' own elaboration of data sourced from WHR 2021.

C Association between inefficiency scores and Happy Planet Index scores

Table 9: Association between HPI and inefficiency scores controlling for life ladder.

	Happy Planet Index	
Cantril ladder	0.224^{*}	(1.77)
inefficiency scores (%)	-0.326^{**}	(-3.23)
Constant	$-9.43e-10$	(-0.00)
N	74	
r^2	0.253	
adj. r^2	0.232	

Note: * $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$. The table reports the coefficients of standardized variables for ease of comparison. Inefficiency scores computed as 1 - technical efficiency multiplied by 100. Thus countries receive a score ranging from 0 to 100, where higher scores indicate higher inefficiency. Source: authors' own elaboration. Data sourced from WHR 2021 and HPI 2021.

D Description of culture zones

Teorell et al. (2019, p. 742), based on Welzel (2013, pp. 23-34), describe the culture zones as follows:

1. "Reformed West" (Western European societies strongly affected by the Reformation);
2. "New West" (overseas offshoots of Western Europe);
3. "Old West" (mostly Catholic parts of Western Europe being core parts of the Roman Empire);
4. "Returned West" (Catholic and Protestant parts of post-communist Europe returning to the EU);
5. "Orthodox East" (Christian Orthodox or Islamic parts of the post-communist world, mostly parts of former USSR);
6. "Indic East" (parts of South and South East Asia under the historic influence of Indian culture);
7. "Islamic East" (regions of the Islamic world that have been parts of the Arab/Caliphate, Persian and Ottoman empires);
8. "Sinic East" (parts of East Asia under the historic influence of Chinese culture);
9. "Latin America" (Central and South America and the Caribbean);
10. "Sub-Saharan Africa" (African countries South of the Sahara).

References

Banker, R. D., Charnes, A., and Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, 30(9):1078–1092.

Barro, R., Lee, J., and Lee, H. (2021). Barro-Lee estimates of educational attainment for the population aged 15-64 from 1950 to 2015. `https://barrolee.github.io/BarroLeeDataSet/BLv3.html`.

Barro, R. J. and Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of development economics*, 104:184–198.

Bernini, C., Guizzardi, A., and Angelini, G. (2013). DEA-like model and common weights approach for the construction of a subjective community well-being indicator. *Social indicators research*, 114(2):405–424.

Binder, M. and Broekel, T. (2012). Happiness no matter the cost? An examination on how efficiently individuals reach their happiness levels. *Journal of Happiness Studies*, 13(4):621–645.

Carboni, O. A. and Russu, P. (2015). Assessing regional wellbeing in Italy: An application of Malmquist–DEA and self-organizing map neural clustering. *Social indicators research*, 122(3):677–700.

Charnes, A., Cooper, W. W., and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, 2(6):429–444.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., and Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer, New York.

De Neve, J.-E., Christakis, N. A., Fowler, J. H., and Frey, B. S. (2012). Genes, economics, and happiness. *Journal of neuroscience, Psychology, and Economics*, 5(4):193.

Debnath, R. M. and Shankar, R. (2014). Does good governance enhance happiness: a cross nation study. *Social indicators research*, 116(1):235–253.

DiMaria, C. H., Peroni, C., and Sarracino, F. (2020). Happiness matters: Productivity gains from subjective well-being. *Journal of Happiness Studies*, 21(1):139–160.

Easterlin, R. (2019). Foreword: Happiness or gdp? In Rojas, M., editor, *The economics of happiness: how the Easterlin paradox transformed our understanding of well-being and progress*, pages v – viii. Springer.

Emrouznejad, A. and liang Yang, G. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*, 61:4–8. Recent developments on the use of DEA in the public sector.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the Penn World Table. *American economic review*, 105(10):3150–82.

Fleurbaey, M. (2009). Beyond GDP: The quest for a measure of social welfare. *Journal of Economic literature*, 47(4):1029–75.

Gower, J. C. (1971). A general coefficient of similarity and some of its properties. *Biometrics*, pages 857–871.

Guardiola, J. and Picazo-Tadeo, A. J. (2014). Building weighted-domain composite indices of life satisfaction with Data Envelopment Analysis. *Social Indicators Research*, 117(1):257–274.

Happy Planet Index (2021). Happy Planet Index methodology paper. www.happyplanetindex.org, Wellbeing Economy Alliance.

Helliwell, J. (2016). Life satisfaction and quality of development. In Bartolini, S., Bilancini, E., Bruni, L., and Porta, P., editors, *Policies for Happiness*, chapter 7, page 149. Oxford University Press.

Helliwell, J. F., Layard, R., and Sachs, J. (2013). *World Happiness Report 2013*. UN Sustainable Development Solutions Network, New York.

Helliwell, J. F., Layard, R., Sachs, J., and De Neve, J.-E. (2021). *World Happiness Report 2021*. UN Sustainable Development Solutions Network, New York.

Lafuente, E., Szerb, L., and Acs, Z. J. (2016). Country level efficiency and national systems of entrepreneurship: a data envelopment analysis approach. *The Journal of Technology Transfer*, 41(6):1260–1283.

Liu, J. S., Lu, L. Y., Lu, W.-M., and Lin, B. J. (2013). A survey of DEA applications. *Omega*, 41(5):893–902.

Lykken, D. and Tellegen, A. (1996). Happiness is a stochastic phenomenon. *Psychological science*, 7(3):186–189.

Mariano, E. B., Sobreiro, V. A., and do Nascimento Rebelatto, D. A. (2015). Human development and Data Envelopment Analysis: A structured literature review. *Omega*, 54:33–49.

Murias, P., Martinez, F., and De Miguel, C. (2006). An economic wellbeing index for the Spanish provinces: A data envelopment analysis approach. *Social Indicators Research*, 77(3):395–417.

Nikolova, M. and Popova, O. (2021). Sometimes your best just ain't good enough: The worldwide evidence on subjective well-being efficiency. *The BE Journal of Economic Analysis & Policy*, 21(1):83–114.

Nissi, E. and Sarra, A. (2018). A measure of well-being across the Italian urban areas: An integrated DEA-entropy approach. *Social Indicators Research*, 136(3):1183–1209.

OECD (2013). *OECD Guidelines on Measuring Subjective Well-being.*

Ravallion, M. (2005). On measuring aggregate "social efficiencyàà. *Economic Development and Cultural Change*, 53(2):273–292.

Rostamzadeh, R., Akbarian, O., Banaitis, A., and Soltani, Z. (2021). Application of DEA in benchmarking: a systematic literature review from 2003–2020. *Technological and Economic Development of Economy*, 27(1):175–222.

Sarracino, F. and O'Connor, K. J. (2021a). Economic growth and well-being beyond the Easterlin paradox. In Bruni, L., Smerigli, A., and DeRosa, D., editors, *A Modern Guide to the Economics of Happiness*, pages 162–188. Edward Elgar Publishing.

Sarracino, F. and O'Connor, K. J. (2021b). Neo-humanism and COVID-19: Opportunities for a socially and environmentally sustainable world. GLO Working Papers series 825, Global Labor Organization.

Schimmack, U. (2008). The structure of subjective well-being. In Eid, M. and Larsen, R. J., editors, *The science of subjective well-being*, volume 54, chapter 6, pages 97–123. The Guilford Press, New York.

Spolaore, E. and Wacziarg, R. (2013). How deep are the roots of economic development? *Journal of economic literature*, 51(2):325–69.

Spolaore, E. and Wacziarg, R. (2018). Ancestry and development: New evidence. *Journal of Applied Econometrics*, 33(5):748–762.

Stiglitz, J. E., Sen, A., Fitoussi, J.-P., et al. (2009). Report by the Commission on the Measurement of Economic Performance and Social Progress. https://ec.europa.eu/eurostat/documents/8131721/8131772/Stiglitz-Sen-Fitoussi-Commission-report.pdf.

Teorell, J., Dahlberg, S., Holmberg, S., Rothstein, B., Khomenko, A., and Svensson, R. (2019). The quality of government standard dataset. http://www.qog.pol.gu.sedoi:10.18157/qogstdjan19.

Tigga, N. S. and Mishra, U. S. (2015). On measuring technical efficiency of the health system in India: An application of Data Envelopment Analysis. *Journal of Health Management*, 17(3):285–298.

Ward Jr, J. H. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American statistical association*, 58(301):236–244.

Welzel, C. (2013). *Freedom rising. Human Empowerment and the Quest for Emancipation.* Cambridge University Press, Cambridge.