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Measuring Multidimensional Inequality in the OECD Member Countries with a Distribution-Sensitive Better Life Index

Koen Decancq

University of Antwerp
Herman Deleeck Centre for Social Policy
Sint-Jacobstraat 2
BE – 2000 Antwerp
F +32(0)3 265 57 98

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ABSTRACT

Abstract. The *Better Life Index* was introduced by the OECD as a tool to chart the multidimensional well-being of its member countries. However, the *Better Life Index* relies only on aggregate country-level indicators, and hence is insensitive to how multidimensional well-being is distributed within countries. This paper discusses how a distribution-sensitive *Better Life Index* could be designed. A broad family of distribution-sensitive *Better Life Indices* is discussed and decomposed in interpretable building blocks. While a rich and comprehensive micro-level data set is necessary to implement the distribution-sensitive *Better Life Index*, no such data set is currently available for all OECD member countries. The paper constructs therefore a 'synthetic' data set that relies on information about macro-level indicators and micro-level data from the *Gallup World Poll*. The implementation of the distribution-sensitive *Better Life Index* is illustrated with this synthetic data set. The illustration indicates that, when taking the distribution of well-being into account, Nordic countries are top-ranked whereas Greece, the Russian Federation and Turkey occupy the bottom positions. The results indicate considerable losses due to multidimensional inequality for OECD member countries. In addition, sizeable differences are found in the level and composition of multidimensional inequality.

Keywords: Better Life Index, Multidimensional well-being, Multidimensional inequality.

JEL Classification: I31, C43, O1.

1 Introduction

A wide consensus has emerged in recent years that GDP per capita, or average income, is not a good measure of overall well-being of a country (Stiglitz et al., 2010). Various measures of well-being have therefore been proposed as alternatives to move 'beyond GDP'. In particular, it has been argued that GDP per capita suffers from two structural problems.

First, GDP per capita is not sensitive to the shape of the distribution and its inequality. The position that all distributional information is irrelevant to evaluate the well-being of a country is a strong one, and arguably not a very appealing one. To include information on the income distribution in the social evaluation, a so-called social welfare measure can be used (for examples, see Atkinson 1970 and many papers in its wake). A social welfare measure penalizes average income for the inequality in its distribution.

Second, GDP per capita includes only information about the incomes of people. It is insensitive to all other dimensions of life that people may care about. This critique has inspired various international institutions to propose their alternative – multidimensional – well-being measures. Two measures are particularly popular. Since 1990, the United Nations Development Programme has published annually its *Human Development Index* (HDI) that contains information on three dimensions: material living standards, life expectancy and educational achievements. More recently, the Organization for Economic Cooperation and Development (OECD) has launched its *Better Life Index* (BLI) which includes 11 dimensions of life (see Boarini and Mira D'Ercole 2013, and Durand 2015 for more details). The two measures differ in scope, with the BLI including a broader set of dimensions for fewer countries than the HDI. Moreover, they take a different perspective with respect to the weighting of the dimensions. The HDI gives equal weights to its three components, whereas the BLI allows a flexible selection of the weighting scheme by means of an interactive web application, the *Your Better Life Index*.[1]

Very few measures address both problems together, i.e. are truly multidimensional and distribution-sensitive. An exception is the inequality-adjusted HDI that has been proposed by Alkire and Foster (2010).[2] Until now, no distribution-sensitive

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1 See www.oecdbetterlifeindex.org. Users of the BLI web application take the perspective of an (impartial) observer and can see how their value judgements about the weights attributed to various well-being dimensions affect the ranking of countries. This approach is more flexible than using a pre-defined weighting scheme. Still, each comparison remains based on the weighting scheme of one single observer. This approach can therefore be argued to be paternalistic (see Decancq et al. 2015). See Decancq and Schokkaert (forthcoming) for a non-paternalistic comparison of well-being in various European countries between 2008-2010.

2 Since 2010, this measure has been yearly published by the UNDP as a complement to the standard HDI. An alternative proposal is made by Hicks (1997).

BLI has been developed by the OECD. This paper discusses whether and how that lacuna may be filled. To do so, the paper proceeds in three steps.

In the first step, the design of a distribution-sensitive *Better Life Index* is discussed by assuming the availability of a 'perfect' data set. This assumption permits to think freely about multidimensional indices and their properties, unhindered by feasibility constraints imposed by data availability. Section 2 makes five concrete recommendations and discusses a family of distribution-sensitive *Better Life Indices* that are consistent with them.[3] To be sufficiently flexible and to capture different normative positions, the proposed index contains three normative parameters: a weighting scheme for the dimensions; a parameter expressing the degree of complementarity between the dimensions; and the degree of inequality aversion of the social aggregation.

Second, a large and broad micro-level data set is needed to implement a distribution-sensitive *Better Life Index* for all OECD member countries. Ideally, the information in this data set should be comparable across countries and consistent with the established and validated macro-level data that are used to compute the original *Better Life Index*. No micro-level data set is currently available that satisfies these requirements. Section 3 discusses how a 'synthetic data set' could be constructed to approximate it. This synthetic data set relies on the broadest micro-level data set that is currently available, the *Gallup World Poll*, and is constructed to be consistent with the available macro-level data.

Using the constructed synthetic data set for 2014 and the index discussed in the first step, Section 4 then implements a distribution-sensitive *Better Life Index*. This exercise shows that Nordic countries are top-ranked, whereas Mexico, Chile, Greece, the Russia Federation and Turkey are at the bottom of the ranking according to the distribution-sensitive *Better Life Index*. For the benchmark normative parameters, losses due to multidimensional inequality are considerable (between 36% and 71%). Finally, a detailed sensitivity analysis discusses the role of the normative parameters.

2 Design of a distribution-sensitive *Better Life Index*

2.1 The family of Better Life Indices

In 2011, the OECD proposed the *Better Life Index* to measure aggregate well-being of its member countries. To be precise, the OECD proposed an entire family of *Better Life Indices* rather than a single index. As in many families, members may look similar and share important features but disagree on some normative matters. Each member of the family of *Better Life Indices* shares the same

3 Recent theoretical advances in the literature on multidimensional inequality will be very useful for our analysis (see Weymark, 2006 and Aaberge and Brandolini, 2015 for surveys).

mathematical structure, but reflects a different position on the philosophical question about the nature of 'the good life'. In particular, the indices disagree on the relative weights that should be given to the different dimensions of life. From the family of indices, the observer – who can be a policy maker, a member of civil society or any citizen – chooses the member that fits best his or her value judgments on the weighting scheme with an interactive web application. This flexible and interactive approach is one of the main innovations of the *Better Life Index* and has a clear advantage: it remains neutral with respect to the value-laden question of selecting the weights of the various dimensions. Contrary to other multidimensional well-being measures such as the *Human Development Index* (HDI), no controversial weighting scheme is imposed upon its users.[4]

I will call the family of Better Life Indices that has been originally proposed by the OECD the 'first generation' *Better Life Indices* ($BLI1$s). These indices take two different pieces of information into account, to measure the overall well-being of a country.

First, descriptive information is needed on the macro-level outcomes of the country in the various dimensions of life. The OECD selected 11 dimensions of life (Boarini et al. 2012 provide a discussion of the selection of the dimensions). These dimensions encompass material living conditions (housing, income, and jobs) and quality of life (community, education, environment, governance, health, life satisfaction, safety, and work-life balance). Most dimensions are measured by more than one indicator, so that in total 24 indicators are considered by the $BLI1$. All these indicators are normalized so that they take values between 0 and 1. When a dimension is measured by more than one indicator, the indicators are first averaged within that dimension with equal weights (see Boarini et al. 2012).

Some notation will be useful in the following. Let l denote the number of dimensions considered. We will refer to the vector of the l normalized macro-level indicators by $m = (m^1, m^2, \ldots, m^l)$. The vector of macro-level indicators is used to construct the macro-level data set X_m (Table 1). To each of the n individuals of a country, the respective vector of macro-level indicators is assigned. A row of the data set, denoted x_i, refers to the outcomes of one individual in the dimensions of life. By construction, all rows of X_m are equal. A column, x^j, refers to the outcomes of all individuals in one dimension.

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4 Ravallion (1997, 2012) and Decancq et al. (2009) provide a critical discussion of the trade-offs implicit in the HDI.

Table 1. A macro-level data set X_m -

	Dim. *1*	…	Dim. l
Individual *1*	m^1	…	m^l
Individual *2*	m^1	…	m^l
…	…	…	…
Individual *n*	m^1	…	m^l

The observer provides the second piece of information by means of an interactive web application. That information reflects her value judgements on the importance of the l dimensions of life. These importance scores are then normalized so that they sum to 1 and define the weighting scheme $\omega = (\omega^1, \omega^2, \dots, \omega^l)$.[5]

Once these two pieces of information are provided, the $BLI1$ aggregates them into a single number. Higher values reflect situations with a higher well-being. The $BLI1$ takes the mathematical structure of a 'mean of means'. More precisely, it can be computed as the mean across all individuals of the weighted mean across the macro-level indicators:

$$BLI1(X_m|\omega) = \sum_{j=1}^{l} \omega^j \times m^j = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{l} \omega^j \times m^j. \quad (1)$$

The right-hand part of expression (1) will be a natural starting point when developing a distribution-sensitive measure. Making this family of well-being indices distribution-sensitive involves a series of small, but structural changes in its design. The resulting new indices will be referred to as the distribution-sensitive Better Life Indices, or the second generation *Better Life Indices* ($BLI2$) for short. Both the descriptive and normative information needs to be adjusted to make the measure distribution-sensitive.

A first condition for the $BLI2$ to capture the distribution of the outcomes is that the data set contains information on the distribution of well-being between individuals. A macro-level data set as X_m does not contain this information. A micro-level data set is therefore necessary. Table 2 presents a micro-level data set, denoted X. Again, rows refer to individuals and columns to dimensions. A cell of the data set, x_i^j, contains the outcome of individual i in dimension j.

Table 2. A micro-level data set X

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5 Mizobushi (2014) proposes a weighting scheme for the BLI based on Data Envelopment Analysis. Markovic et al. (2015) discuss the weighting scheme of the Better Life Index using a so-called i-distance approach. Kasparian and Rolland (2012) provide a sensitivity analysis of the ranking of the countries based on the choice of weights. They observe a limited role for the weighting scheme on the overall ranking of the countries.

	Dim. *1*	…	Dim. l
Individual *1*	x_1^1	…	x_1^l
Individual *2*	x_2^1	…	x_2^l
…	…	…	…
Individual *n*	x_n^1	…	x_n^l

Based on the micro-level data set X, the vector $\mu = (\mu^1, \dots, \mu^l)$ can be derived. This vector contains, for each dimension, the mean obtained from the micro-level data. In analogy to the macro-level data set X_m a new data set can be constructed that assigns to each individual the vector μ. This smoothed data set will be denoted X_μ. It can be obtained from X by performing in each dimension a sequence of progressive transfers until the distribution in each dimension is perfectly smoothed and completely equal.

In general, the macro-level data set X_m and the smoothed data set X_μ need not to coincide. The (statistical) difference may come from measurement or sampling error in the micro-level data, or because the definition of the micro and macro-level indicators is different. For example, the income per capita measures in national accounts may not coincide with the average income from micro-level household income surveys even when including the same set of income components. It is important to distinguish between the statistical difference that comes from the inconsistencies between micro and macro-level data from the normative difference that stems from the inclusion of the distributional information.

Second, the normative information that is provided by the observer also needs to be enriched with additional normative parameters. These parameters will capture the value judgments of the observer concerning the distribution of the outcomes, in particular on the desired degree of complementarity between the dimensions of life and the aversion towards multidimensional inequality. Section 2.3 discusses these parameters in detail. First, however, we discuss the general structure of the index.

2.2 The distribution-sensitive Better Life Index as double aggregation

A distribution-sensitive *Better Life Index* aggregates across the dimensions and the individuals of the micro-level data set, taking the value judgments of the observer into account. In general, such a double aggregation can be done according to two procedures.[6]

In the first procedure, one aggregates first across the dimensions of life to reach a well-being index W_i for each individual i. Then, in a second step, the resulting well-being indices are aggregated across the individuals. This procedure is most standard in welfare economics, and it reflects an individualistic perspective to well-being (Kolm 1977).

Alternatively, the sequence can be reversed. This leads to a second procedure. One aggregates first across the individuals in each dimension to obtain a summary statistic S^j for each dimension j. Then, in the second step, the summary statistics are aggregated across the dimensions. This procedure is used by many composite indices (for instance the HDI).

In general, the two procedures will lead to different results. In fact, only in specific cases will results according to both sequences coincide. The first generation $BLI1$ is an example of such a specific case. We will return to these specific cases below.

Which procedure is preferable? Table 3 provides an illustration with two countries that will be helpful to make up our mind about the desirability of both procedures. For this example, we assume that there are two dimensions of life $(l = 2)$. Both countries have three citizens $(n = 3)$. When looking at country A (on the left), it can be seen that individual 1 is worst off in dimension 1 and that individual 3 is worst off in dimension 2. Individual 2 scores relatively well on both dimensions. Now, compare this country to country B (on the right). In country B, individual 1 is bottom ranked on both dimensions, while individual 2 is second ranked on both and individual 3 is top-ranked.

6 For a more formal discussion of the double aggregation problem, see Kolm (1977), Dutta et al. (2002), Pattanaik et al. (2012), Decancq and Lugo (2012), and Decancq (2014) amongst others.

Table 3. Comparing two countries with different correlation between the dimensions of life

	Country A		Country B	
	Dim. *1*	Dim. *2*	Dim. *1*	Dim. 2
Individual *1*	0.1	0.5	0.1	0.1
Individual *2*	0.4	0.4	0.4	0.4
Individual *3*	0.5	0.1	0.5	0.5

In this example, the distributions for the two dimensions are exactly the same in both countries (they are equal to (0,1; 0,4; 0,5) in all cases). Yet, the correlation between the dimensions of life is different in both societies. In country A, individuals doing well in one dimension perform poorly in the other, and the correlation between the dimensions of life is low (even negative), whereas in country B the same individuals are at the top and bottom in each dimension, i.e. the correlation among outcomes at the individual level is much higher. We say that country B is obtained from country A by means of a so-called 'correlation increasing switch'.[7]

Most people will agree that the correlation between dimensions of life matters for welfare comparison of countries in Table 3.[8] To allow this difference to play a role, the double aggregation described above cannot follow the second procedure. Indeed, in the first step of the procedure, all information about the correlation is lost, which makes the second procedure insensitive to correlation. The first procedure, which does not suffer from this problem, is therefore preferred.

The concern for the correlation between the dimensions of life strengthens the data requirements further. A perfect data set should not only contain micro-level information on the distribution of each dimension separately; in addition it should also contain information on the correlation between the dimensions of life across individuals. In other words, all information should come from a single micro-level data set that covers all dimensions for all individuals in the same country; and

7 A 'correlation increasing switch' reshuffles the multidimensional outcomes of two individual so that one becomes top-ranked in all dimensions and the other bottom-ranked (see Tsui, 1999 for a formal definition). In Table 3, country B is obtained by a correlation increasing switch from country A between individual 1 and 3.

8 The sensitivity to correlation plays an important role in the literature on multidimensional inequality (see Atkinson and Bourguignon, 1982; Dardanoni, 1996; Tsui, 1999; Ferreira and Lugo, 2013; and Decancq, 2014 amongst others). Tarroux (2015) finds that students are averse to correlation in a questionnaire study about multidimensional inequality.

such data set should cover, in a comparable way, all OECD countries. In practice, finding such a broad data set is a huge hurdle, as described in Section 3.

2.3 Incorporating value judgments

The previous section argued that the preferred sequence for aggregating is first across dimensions of life and then across people. This section discusses how to perform these two aggregations precisely.

We will call the function that performs the aggregation across dimensions the 'well-being function' WB. In principle, the weighted mean formula of the $BLI1$ as given by expression (1) could be used as well-being function. Yet, it is useful to generalize the arithmetic mean a bit further. The generalized mean is a natural generalization of the arithmetic mean, and provides a well-being function that is flexible with respect to the value judgement of the observer concerning the complementarity between the various dimensions of life. It is defined as follows:

$$W_i = WB(x_i|\omega,\beta) = \left(\sum_{j=1}^{l} \omega^j \times \left(x_i^j\right)^{1-\beta}\right)^{\frac{1}{1-\beta}}. \quad (2)$$

The parameter β captures the value judgement of the observer concerning the degree of complementarity between the dimensions of life. The generalized mean has a long pedigree in measurement theory and economics (where it is known as a CES utility function) and has been often proposed to measure well-being of an individual.[9] Various interesting special cases can be reached by adjusting the normative parameter β.

The (familiar) case of the arithmetic mean used in the $BLI1$s is obtained when β is set equal to 0. The arithmetic mean assumes perfect substitutability between the dimensions. In this case, an individual can be assumed to perfectly compensate a low outcome in one dimension by a higher outcome in another dimension. A decrease of outcomes in dimension 1 of 0.01 units, for instance, can be compensated by an increase in dimension j of $0.01 \times (\omega^1/\omega^j)$ units. This assumption may lead countries to specialize in 'easy' dimensions and may result in unbalanced well-being. Some observers have criticized this feature and suggested that a lower degree of substitutability is more appropriate.

Another interesting (limit) case is obtained when the observer sets β equal to 1. The well-being function is then a geometric mean and the aggregation becomes multiplicative rather than additive. This specification is known by economists as

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9 Blackorby and Donaldson (1982) provide an axiomatic characterization of this mathematical structure. Maasoumi (1986, 1999) proposes the generalized mean based on considerations from information theory. Anand and Sen (1997) use it as building block in their multidimensional poverty measure and Decancq and Lugo (2012, 2013) discuss its use as multidimensional well-being index.

the Cobb-Douglas utility function.[10] In this multiplicative expression, the trade-offs depend not only on the relative weights but also on the levels of the outcomes. A decrease of the outcome in dimension 1 of 1 per cent can be compensated by an increase in dimension j of (ω^1/ω^j) per cent.

Increasing the degree of complementarity, captured by the normative parameter β, makes it increasingly difficult to compensate a decrease in one dimension by an increase in another. In the end, when β approaches ∞ we obtain that the well-being of an individual is determined by the worst outcome across all dimensions of life. Increasing the outcomes in any other dimension does not affect well-being. A policy maker who wants to improve the well-being of an individual has to focus on her worst outcome. This leads automatically to a more balanced development.[11]

Introducing both parameters together leads to a flexible well-being function. By choosing particular values for the parameters ω and β, the trade-offs between the dimensions are fixed. Only in the case where the aggregation is linear ($\beta = 0$), the trade-offs depends only on the weights. In general, the choice of the parameter β determines the implied trade-offs (see Decancq and Lugo, 2013 for a discussion).

Once a well-being index for each individual is obtained, the next step is to aggregate them to obtain an overall well-being score for the country as a whole. A social welfare function, SW, performs that second aggregation. Social welfare functions have been extensively studied in the literature. We work with a standard social welfare function, proposed by Atkinson (1970)

$$SW(W_i|\varepsilon) = \left(\frac{1}{n}\sum_{i=1}^{n} W_i^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}. \tag{3}$$

This function is again based on a generalized mean (as can be seen by comparing expression 2 and 3). The normative parameter ε now captures the observer's aversion to inequality. By setting this parameter equal to 0, the social welfare function becomes an (unweighted) average of the individual well-being indices. This reflects the position of an inequality-neutral observer who does not care about the shape of the distribution. This inequality neutral position is implicit in the first generation of BLI's.

Increasing the parameter ε, increases the weight given to what happens at the bottom of the distribution. In the limit, when ε becomes very large, a Rawlsian social welfare function is obtained that equals the outcome of the worst-off individual in society. The inequality aversion is an essential parameter of the distribution-sensitive *Better Life Index*.

10 This specification has been used by UNDP to compute the HDI after its revision in 2010.

11 Lorzano Segura and Gutierrez Moya (2010) advocate this limit case for a well-being measure.

2.4 The distribution-sensitive Better Life Index defined

Once the functional specifications of both aggregations are chosen, the distribution-sensitive *Better Life Index* can be assembled by substituting expression (2) in expression (3). This leads to the following expression

$$BLI2(X|\omega,\beta,\varepsilon) = \left[\frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{l}\omega^{j}\times\left(x_i^j\right)^{1-\beta}\right)^{\frac{1-\varepsilon}{1-\beta}}\right]^{\frac{1}{1-\varepsilon}}. \quad (4)$$

This index takes as inputs a micro-level data set X and three normative parameters: the weighting scheme ω, the degree of complementarity β, and the inequality aversion ε. It has been proposed in the literature on multidimensional social welfare and inequality measurement by Bourguignon (1999).[12]

When comparing expression (4) with expression (1), it is clear that this second generation BLI is a close relative of the first generation BLIs. There are two important differences, however. First, the data set is different: the $BLI2$ makes use of a micro-level data set X, whereas the $BLI1$ is based on macro-level data set X_m. Second, there are two additional normative parameters, β and ε, which give observers the flexibility to customize the index in accordance to their value judgments on the distribution of outcomes. Yet, when these additional parameters are both set at the value 0, and the measure is computed based on the macro-level data set X_m, then both measures coincide.

At this point it is useful to reconsider the concern for correlation between the dimensions of life across individuals. We have seen that the aggregation procedure recommended (first across dimensions, and then across individuals) gives a prominent role to this correlation when measuring well-being, contrary to the alternative procedure that changes the sequence of aggregation. How and to what extent the obtained index is sensitive to the correlation is determined by the relative values of both normative parameters β and ε. Bourguignon (1999) shows that whenever $\varepsilon > \beta$, an increase in the correlation between the dimensions (by means of a correlation increasing switch) lowers the well-being measure. The higher the selected complementarity between the dimensions, the higher the inequality aversion has to be, for an increase in correlation to lead to a decrease of the $BLI2$ (i.e. a social welfare decline).

When ε equals β, the index is invariant to correlation. This choice received some attention in the literature and has been used by the UNDP to define their inequality-adjusted HDI.[13] This special case deserves a closer look. When both parameters are equal, we obtain the following simplified expression

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[12] Various papers discuss this multidimensional social welfare measure (or one of its special cases), e.g. Tsui (1995), Foster et al. (2005), Decancq and Ooghe (2010), Seth (2013), and Bosmans et al. (forthcoming).

[13] Foster et al. (2005) propose a closely related index as a distribution-sensitive well-being measure and study its properties.

$$BLI2(X|\omega, \varepsilon, \varepsilon) = \left[\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{l}\omega^{j} \times \left(x_i^j\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}. \tag{5}$$

Inspecting this expression, it is clear that both summation signs can be exchanged without affecting the result. In other words, when ε equals β, both aggregation procedures lead to the same result. As a consequence, the simplified index is invariant to correlation between the dimensions of life. This simplification allows the data set to be constructed from different data sources, each providing distributional information for one single dimension. This is the main practical advantage of the simplified measure.

Yet, is the simplification normatively appealing? To address this question it is useful to remind readers of the precise interpretation of both parameters. The parameter β captures the degree of complementarity between the dimensions, i.e. whether they can be seen as perfect substitutes ($\beta = 0$) or as complements (for larger values of β). The parameter ε, on the other hand, captures the inequality aversion of individuals (the larger ε, the larger the aversion to inequality). Both parameters capture a very different aspect of the multidimensional evaluation. There is no reason why both normative parameters should be equal. Both normative parameters play a separate role and have their own *raison d'être*. Equalizing them *a priori* is a very strong requirement. It seems therefore more appealing to work with the flexible measure (expression 4) rather than the simplified one (expression 5).

2.5 Decomposing the distribution-sensitive Better Life Index

The distribution-sensitive *Better Life Index* can be decomposed in different components that have specific interpretations. A first decomposition expresses the distribution-sensitive $BLI2$ as a product of the 'potential $BLI2$' and the 'loss due to multidimensional inequality'.[14]

$$\underbrace{BLI2(X|\omega,\beta,\varepsilon)}_{\substack{distribution- \\ sensitive \\ BLI2}} = \underbrace{BLI2(X_\mu|\omega,\beta,0)}_{Potential\ BLI2} \times \left[1 - \underbrace{\left(1 - \frac{BLI2(X|\omega,\beta,\varepsilon)}{BLI2(X_\mu|\omega,\beta,0)}\right)}_{\substack{loss\ due\ to \\ multidimensional \\ inequality}}\right]. \tag{6}$$

Even though this decomposition is a simple accounting equation, it is interesting because it brings to the fore the loss due to multidimensional inequality. The potential $BLI2$ is the $BLI2$ of the smoothed data set X_μ rather than the actual micro-level data set X. Potential well-being equals total well-being when inequality within each dimension could be eliminated without any cost. The potential $BLI2$ does not depend on the inequality aversion parameter ε, but does depend on the normative parameters ω and β.

14 Alkire and Foster (2010) discuss a similar notion of a 'potential HDI'.

The second term of the decomposition, the loss due to multidimensional inequality, ranges between 0 and 1 and can be interpreted as a percentage.[15] The larger the inequality in the micro-level data set X, the larger the measure. In addition, the larger the inequality aversion parameter ε, the larger is the loss due to multidimensional inequality.

This decomposition highlights in a natural and intuitive way the fundamental trade-off between average outcomes and the inequality of the well-being distribution. The potential $BLI2$ depends on the smoothed data set X_μ and measures the averaged well-being, whereas the loss due to multidimensional inequality captures the loss in $BLI2$ due to the shape of the multidimensional distribution.

The 'loss due to multi-dimensional inequality' in equation (11) can be decomposed further into two elementary building blocks: the loss due to inefficiency and the loss due to inequity.

$$\left[1-\underbrace{\left(1-\frac{BLI2(X|\omega,\beta,\varepsilon)}{BLI2(X_\mu|\omega,\beta,0)}\right)}_{\substack{loss\ due\ to\\ multidimensional\\ inequality}}\right]=\left[1-\underbrace{\left(1-\frac{BLI2(X|\omega,\beta,0)}{BLI2(X_\mu|\omega,\beta,0)}\right)}_{\substack{loss\ due\ to\\ multidimensional\\ inefficienty}}\right]\times\left[1-\underbrace{\left(1-\frac{BLI2(X|\omega,\beta,\varepsilon)}{BLI2(X|\omega,\beta,0)}\right)}_{\substack{loss\ due\ to\\ multidimensional\\ inequity}}\right]. \qquad (7)$$

Again, this decomposition is based a simple accounting equation, but it offers interesting insights in the composition of multidimensional inequality. The loss due to multidimensional inequity captures the dispersion in the well-being levels of individuals within a country, whereas the multidimensional inefficiency measures the loss due to the potential mutual beneficial exchanges. Indeed, two individuals with different outcomes in the dimensions of life but with the same well-being level (i.e when there is no multidimensional inequity), could both improve their situation if it were possible for them to exchange some outcomes. The loss due to multidimensional inefficiency captures the latter effect. In fact, some observers have argued that the multidimensional analysis should be concerned with inequity alone, and not with inefficiency, and the decomposition in expression (7) allows them to do so (see Bosmans et al. (forthcoming) for a detailed discussion).

3 Data for the distribution-sensitive Better Life Index

The previous section assumed that a perfect data set was available. We have seen that such a perfect data set has to satisfy several stringent conditions. First, it should be a large micro-level data set with information about the selected dimensions of life for a representative sample of citizens of all countries of

[15] The loss due to multidimensional inequality was initially proposed by Kolm (1977) as a 'normative measure of multidimensional inequality'. See Weymark (2006) for a survey of the literature on normative multidimensional inequality measures. Bosmans et al. (frthc) give a critical discussion of its interpretation.

interest.[16] Second, the micro-level data set should be consistent with the 'official' and validated macro-data sources whenever they are available. Third, it should satisfy standard requirements of statistical quality such as comparability across countries, timeliness, etc. (Boarini et al. 2012).

Unfortunately, no single data set currently meets all these requirements. The data set that presumably comes closest to satisfying these conditions is the *Gallup World Poll*. This survey includes most of the countries of interest. While not all 11 dimensions of the *Better Life Index* are covered equally well by the *Gallup World Poll*, for most dimensions a reasonable proxy is available. The main disadvantage of the data set is that it is collected by the private company Gallup and that access is limited, which makes scientific validation and systematic replication of the results by different researchers virtually impossible. Moreover, both the sampling procedure and the small sample size of the survey affect the quality of the survey (Gasparini and Glüzmann, 2012). For these reasons, the *Gallup World Poll* cannot be considered as a perfect micro-level data set.

In absence of a perfect micro-level dataset, the first-best solution would arguably be to collect the missing data. Given the size and broadness of the ideal micro-level dataset, this strategy is likely to be very costly. A second-best strategy is to construct a so-called 'synthetic' micro-level data set. This data set would be constructed so as to be consistent with the pieces of well-being information that are available from different existing data sets. Constructing a complete synthetic data set based on scattered pieces of information requires some – arguably strong – assumptions. This section provides an illustration of how this could be done using two pieces of information that we have discussed earlier. First, there is the 'official' and validated vector $m = (m^1, m^2, \ldots, m^l)$ containing (mainly) macro-level data that are currently used to compute the $BLI1$. Second, the *Gallup World Poll* can be used, as it provides information about the distribution of most of the 11 dimensions of well-being and on the correlation between the well-being outcomes at the individual level.

Combining information about the average outcome from a macro source with distributional information from a micro source is common practice in the one-dimensional literature on global income inequality.[17] In these studies, the mean of the income distribution of a country is anchored on information from its national accounts (e.g. on its GDP per capita), while information about the shape of the distribution comes from micro income data obtained from household surveys (or from parametric models estimated based on these surveys). The simplest procedure to construct such a synthetic data set is to rescale or uprate all incomes in the household survey with a factor that equals the ratio between macro variable (e.g. GDP per capita) and the average income from the household survey. This procedure assures that the average of the resulting synthetic distribution

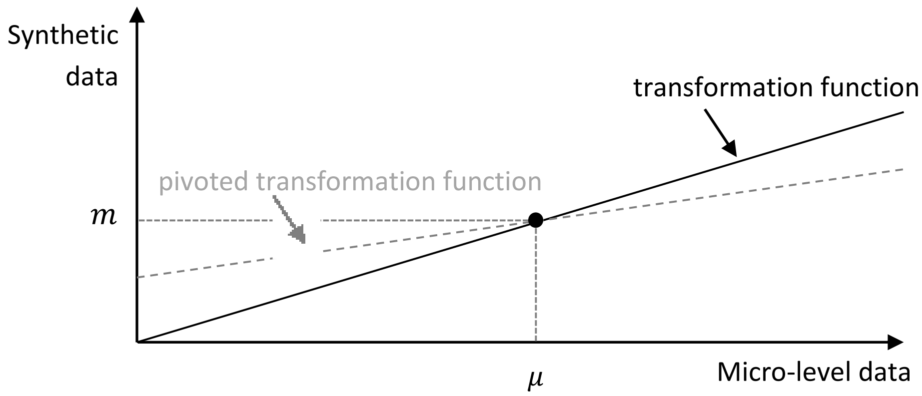
[16] In our setting, these are the OECD member countries and some emerging economies such as Brazil, Russia, India, China, and South Africa (the so-called BRICS countries).

[17] Anand and Segal (2008) provide a survey and a critical discussion of this procedure.

correspondents perfectly to the 'official' information from the national accounts. In addition, the inequality of the synthetic distribution (measured by a relative inequality index such as the Gini coefficient, for instance) remains consistent with that from the household surveys.

This paper constructs a multidimensional synthetic data set based on two sources (a validated macro-level data set, i.e. the one used by the OECD for the *Better Life Index*; and a micro-level data set, the *Gallup World Poll*) inspired by the approach used in the literature on global income inequality. In this approach, the variables from the *Gallup World Poll* are rescaled so that their averages match the validated macro information. Figure 1 illustrates the procedure for a single variable. The micro-level data from *Gallup World Poll* (together with their average μ) are plotted on the horizontal axes. A linear transformation function (the black full line on Figure 1) rescales all micro-level data by the factor m/μ. The synthetic data can then be read on the vertical axis. The average of the synthetic data coincides with m, the validated macro-level information about the average. Moreover, as the increasing transformation function does not change the ranking of the individuals in each dimension, the (rank) correlation structure between the different dimensions of life of the synthetic data set coincides with that from the underlying micro-level data set.

Figure 1. Transformation of the micro-level data into a synthetic variable with the same mean as in the macro-series



Let us discuss the implementation of this procedure in more detail, starting from the macro-level data set. For 10 out of the 11 dimensions of the $BLI1$, the approach relies on the validated macro-level variables as collected and validated by the OECD for the $BLI1$ (see Table 4, left column; these 10 dimensions are denoted with a *).[18] Since the macro-level data are available for each country by gender, the approach considers separately, for each country, its female and male population.

[18] Data were last updated on 3/12/2014.

The method illustrated in Figure 1 above is hence applied to each of these groups separately.

For the purpose of measuring well-being and its inequality, two modifications of the normalization procedure followed by the OECD for the $BLI1$ have been made. First, the linear normalization used by the OECD to map the outcomes in each variable between 0 and 1 is replaced by a simple rescaling of the variables by their maximal value. Loosely speaking, the latter modification provides some space in the relevant positive interval of a distribution around its average performance also for the worse performing countries. Second, the indicator used by the OECD to measure *Personal Security* (homicide rates) has been changed to a more micro-oriented variable, i.e. self-reported safety.[19]

Concerning the micro-level data, four waves of *Gallup World Poll* (2010-2013) have been pooled for each country considered. Data have been pooled across four waves to enlarge sample sizes. The analysis retains only individuals for whom information is available for all well-being dimensions, which leads to sample sizes of about 900 respondents in Norway and 9,000 in the Russian Federation. In Table 4 (right column), the indicators from the *Gallup World Poll* which are used to approximate the joint distribution are denoted with (**). Whenever more than one indicator from the *Gallup World Poll* has been used for one dimension, the indicators are first averaged at the individual level (using equal weights).

Before proceeding to the results, three comments about the synthetic data should made.

First, as is clear from Table 4, no good proxy is available in the *Gallup World Poll* for three well-being dimensions ('Housing', 'Work/Life Balance', and 'Civic Engagement'). For these dimensions, their distribution is assumed to perfectly equal across individual. The rescaling procedure illustrated in Figure 1 then results in a synthetic variable where all individuals have the macro indicator of their country, as for the $BLI1$.[20]

Second, for the dimension 'Income and Wealth', some additional (and validated) distributional information is available. The OECD collects data on income distribution in its Income Distribution Database (IDD). The micro-level data from *Gallup World Poll* are not always well-aligned with the information in the IDD database. Some further adjustment of the *Gallup World Poll* income data is therefore desirable. A similar method can be used to adjust the Gini coefficient of the synthetic data to match that from the validated source (IDD). See Figure 1.

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19 Decancq (2015) describes these modifications and their effect on the results in more detail.

20 This assumption may introduce a bias when estimating multidimensional inequality. The direction of the bias is not certain, however, as there the missing dimensions may be negatively correlated with the observed dimensions: in this case, the consideration of their inequality may reduce multidimensional inequality when measured with a correlation-sensitive measure (that is when $\varepsilon > \beta > 0$).

Rather than the black full transformation function, the gray dashed transformation function is used. This new transformation function is obtained by pivoting the original one around the point (μ, m), which assures that the average of the synthetic income distribution remains fixed at the macro-level indicator m. The lower slope of the grey dashed line compared to the black line implies a reduction of the inequality of the synthetic income variable. By selecting the appropriate slope for the pivoted transformation function, the Gini coefficient of the synthetic data can be matched to the external distributional information. The extent of pivoting necessary to achieve this result differs across countries.

Third, for almost all dimensions in Table 4, the variable used in columns 2 and 3 are not precisely identical. This discrepancy implies that the method used assumes that the distributional shape of the variable in column 3 provides a reasonable approximation of the shape of the distribution for the variable in column 2. In the case of education, for example, each individual with a high number of years of schooling (the micro-level variable measured by *Gallup World Poll*) is assumed to have a high score on the BLI macro indicator, which is constructed as an average of the variables 'educational attainment', 'education expectancy' and 'students' cognitive skills'. Without additional information it is hard to judge how reasonable this and related assumptions really are.

In line with the discussion of Section 2, the synthetic data is called X. Summary statistics are provided in Appendix. Table 5 and 6 show the (rank) correlation matrix for Austria and the United States. In each cell the Spearman rank correlation coefficient is reported. These tables show how the correlation structure between the dimensions of life (captured by micro-level data set) is remarkably different. The correlation between the positions of the non-income dimensions and income is much higher in the United States compared to Austria. Richer individuals in the United States are more likely to occupy the top positions in the other dimensions of life as well.

Table 4. Overview of the variables used to construct a synthetic well-being dataset from different sources

Dimension	Information about mean from validate macros sources	Information about distribution
Income and Wealth	Household net adjusted disposable income and Household net financial wealth (*)	Distribution of (Imputed) income per capita (**) linearly transformed to match validated Gini Coefficient (of income after taxes) (*)
Jobs and Earnings	Employment rate, Personal earnings, Employment insecurity, and Long-term unemployment rate (*)	Distribution of an indicator of Employment (**)
Housing	Number of rooms per person, Housing expenditure, and Dwellings without basic facilities (*)	Equal distribution assumed
Health	Life expectancy at birth and Self-reported health (*)	Distribution of mean of indicator of Satisfaction with health and Absence of health problems (**)
Work/Life Balance	Employees working very long hours and Time non-worked (*)	Equal distribution assumed
Education and Schooling	Educational attainment, Education expectancy, and Students' cognitive skills (*)	Distribution of Years of schooling (**)
Social Connections	Social network support (*)	Distribution of indicator of Social network support (**)
Civic Engagement	Transparency of governance and Voter turn-out (*)	Equal distribution assumed
Environmental Quality	Satisfaction with water quality and air pollution (*)	Distribution of mean of indicator of Satisfaction with water quality and air pollution (**)
Personal Security	Self-reported safety (**)	Distribution of mean of indicator of Self-reported safety (**)
Subjective Well-Being	Life satisfaction (*)	Distribution of Life satisfaction (**)

Note: All BLI macro variables are computed by the OECD as weighted averages of normalised variables shown in column 2.
Legend: (*) Macro-level data from OECD (2014).
(**) Micro-level data from *Gallup World Poll* (2010-2013).

Table 5. Spearman rank correlation matrix for the eight non-equal dimensions based on the synthetic data (Austria)

Austria	Income and Wealth	Jobs and Earnings	Health	Education and Schooling	Social Connect-ions	Environ-mental Quality	Personal Security	Subjective Well-Being
Income and Wealth	1							
Jobs and Earnings	0.0608*	1						
Health	0.0467*	-0.4639*	1					
Education and Schooling	0.1648*	-0.3931*	0.3414*	1				
Social Connections	-0.00910	0.6476*	-0.4519*	-0.4006*	1			
Environmental Quality	0.00240	-0.4845*	0.4031*	0.2925*	-0.5251*	1		
Personal Security	0.0212	-0.4342*	0.3908*	0.3137*	-0.4318*	0.4453*	1	
Subjective Well-Being	0.0857*	0.0843*	0.1055*	0.0484*	0.1613*	0.0104	0.0365*	1

Note: * denotes significant differences from 0 ($p < 0.05$)

Table 6. Spearman rank correlation matrix for the eight non-equal dimensions based on the synthetic data (United States)

United States	Income and Wealth	Jobs and Earnings	Health	Education and Schooling	Social Connect-ions	Environ-mental Quality	Personal Security	Subjective Well-Being
Income and Wealth	1							
Jobs and Earnings	0.0930*	1						
Health	0.0847*	-0.3146*	1					
Education and Schooling	0.2399*	-0.2176*	0.2993*	1				
Social Connections	0.0305	-0.5052*	0.4802*	0.4181*	1			
Environmental Quality	0.0605*	-0.3360*	0.3871*	0.2699*	0.5561*	1		
Personal Security	0.0517*	-0.2199*	0.2836*	0.2702*	0.3653*	0.3196*	1	
Subjective Well-Being	0.1875*	0.1105*	0.1786*	0.0797*	0.0178	0.0566*	0.0740*	1

Note: * denotes significant differences from 0 ($p < 0.05$)

4 Implementation of the distribution-sensitive Better Life Index with a synthetic data set

4.1 The distribution-sensitive Better Life Index for 2014

As described in Section 2, computing a distribution-sensitive *Better Life Index* requires not only a large data set, but also making choices on the three normative parameters ω, β and ε (see equation 8). As, for practical reasons, it is impossible to show results for all possible normative parameter values, the empirical results described in this section use as weighting scheme (ω) the average weights given by the registered users of the *Better Life Index* web-site.[21] These weights are shown in Figure 2. Even though the default option for the users is an equal weighting scheme, it is clear that users gave higher weights to 'Health' and 'Subjective Well-Being', and lower weight to the dimension 'Civic Engagement'.

Figure 2. Average weighting scheme of the users of the Better Life Index website

We start our discussion of the results for particular values of the two normative parameters. The degree of complementarity β is first set at a value of 1. This makes the aggregation multiplicative. The value of the inequality aversion parameter ε is set at 2. This choice implies a considerable inequality-aversion. These parameter values introduce an aversion to correlation in the index, since we have that $\varepsilon > \beta > 0$. Later in this section we will relax these parameter choices and see how the results change when different values for β and ε are selected.

Figure 3 provides the key result of this section. It shows the $BLI2$ and the potential $BLI2$ for the countries considered, with countries ranked according to their $BLI2$ (the overall well-being of each country while taking the well-being distribution into account). The potential $BLI2$ measures total well-being if the inequality in each

21 The data are collected in June 2013 and include more than 37,700 responses.

dimension could be eliminated without any cost. The well-being loss due to multidimensional inequality is given by 1 minus the ratio between both measures multidimensional (recall the decomposition in equation 11). This loss is shown in Figure 4. For the selected normative parameters, losses are considerable and range between 36% and 71% for Austria and Turkey, respectively. The level of this loss obviously depends on the choice of the normative parameters.

Not surprisingly, Sweden, Austria, Netherlands, Denmark and Norway are the countries with the highest $BLI2$. Mexico, Brazil, Mexico, the Russian Federation, Greece and Turkey are at the bottom of the ranking. When looking at the top-five performers in Figure 3, the potential $BLI2$ of Norway is higher than the one of Austria, whereas Austria has a higher $BLI2$. The loss due to multidimensional inequality is larger in Norway as compared to Austria (see Figure 4). In general, countries at the bottom of the $BLI2$ ranking also have a larger loss due to multidimensional inequality. This means that countries with worse well-being performance combined both low average scores for the various dimensions of life and high multidimensional inequality. A similar pattern is highlighted by the inequality-adjusted HDI (UNDP, 2014).

Column 1 and 2 of Table 7 presents $BLI2$ and potential $BLI2$ for all countries. The ranking of each country according to each variable is shown in italics. Although the rank-correlation between $BLI2$ and potential $BLI2$ is relatively high (Spearman's rank correlation coefficient is 0.93), the ranking of some countries is affected strongly when taking the multidimensional well-being distribution into account. The United States loses 7 positions, whereas Austria gains 11, for instance. This re-ranking is entirely driven by the loss in $BLI2$ due to multidimensional inequality (as shown in column 3 of the table).

Finally, Figure 5 plots both components of the 'loss due to multidimensional inequality' for each country (recall the decomposition in expression (7)). The horizontal axis shows the loss due to inequity (i.e the dispersion in well-being levels between the individuals), whereas the vertical axis presents the inefficiency component (i.e the potential mutually beneficial exchanges). Overall losses due to multidimensional inequality are larger for countries in the top right-hand corner of the figure (e.g. Turkey and Greece). For most countries, inequity and inefficiency account in roughly equal parts for the loss due to multidimensional inequality. In other words, the loss due to multidimensional inequality does not only consist of inequity, but also the inefficiency component contributes to the total loss due to multidimensional inequality. Comparisons based on multidimensional inequality do not necessarily correspond to comparisons of multidimensional equity. Compare the United States and Iceland on Figure 4 for instance. Iceland records a larger loss due to multidimensional inequality than the United States (52% versus 45%), yet the well-being differences in the United States are larger (in Figure 5, the United States has a higher loss due to inequity compared to Iceland).

4.2 Sensitivity Analysis

How do results change for other choices of the normative values? The last three columns of Table 7 show the results for an alternative case with (ε=1 and β=0.5). In this case both the degree of complementarity and inequality aversion are lower than in the benchmark case. Also losses due to multidimensional inequality are much lower. This finding illustrates that the order of magnitude of the loss due to multidimensional inequality is sensitive to the normative parameters and should be interpreted with care.

How sensitive the results are with respect to the normative parameters can be illustrated in the case of Austria and the United States, two countries with very different ranking based on $BLI2$ and potential $BLI2$ (see Figure 3).

Figure 3. The BLI2 and the potential BLI2 (ε=2 and β=1)

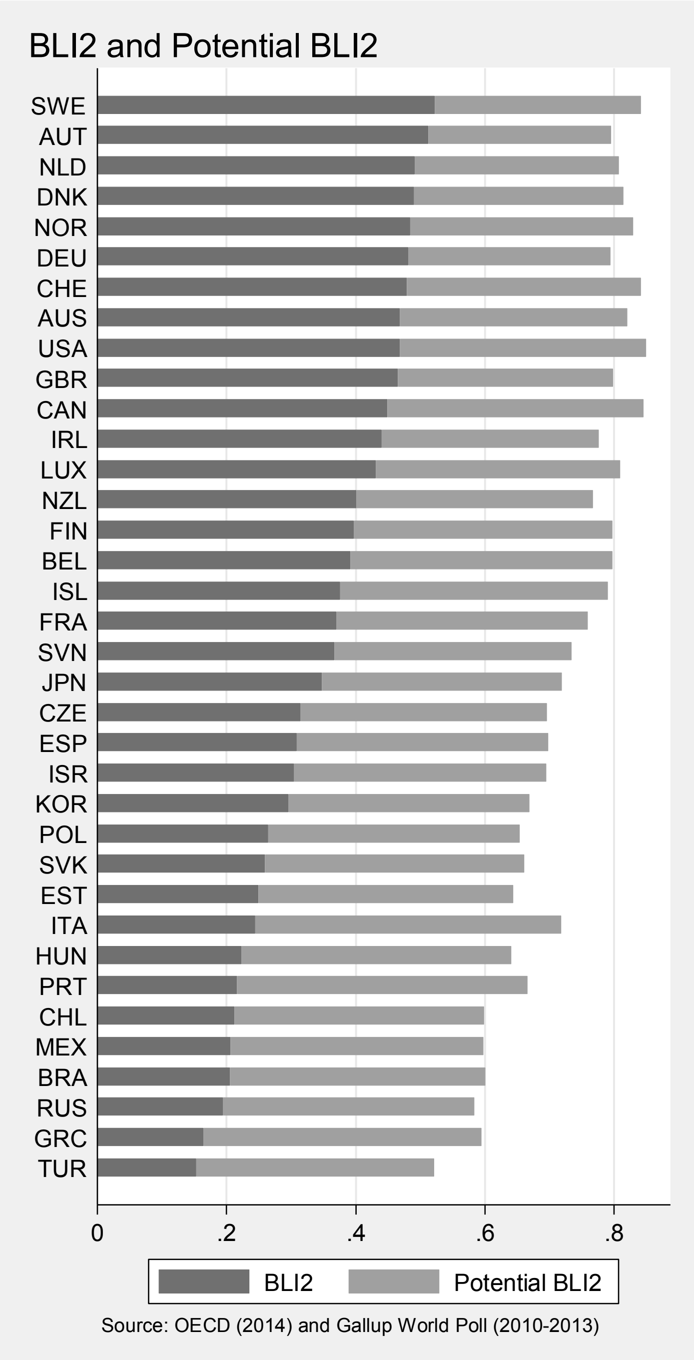


Figure 4. BLI2 loss due to multidimensional inequality (ε=2 and β=1)

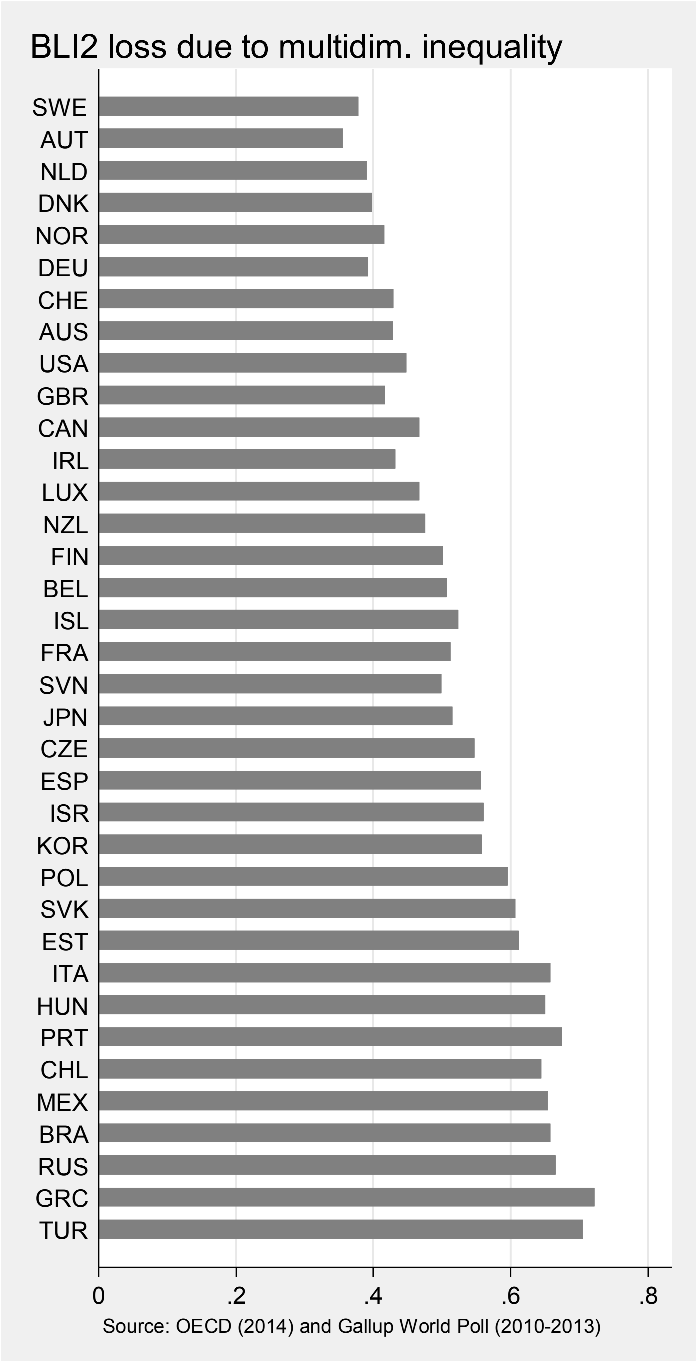
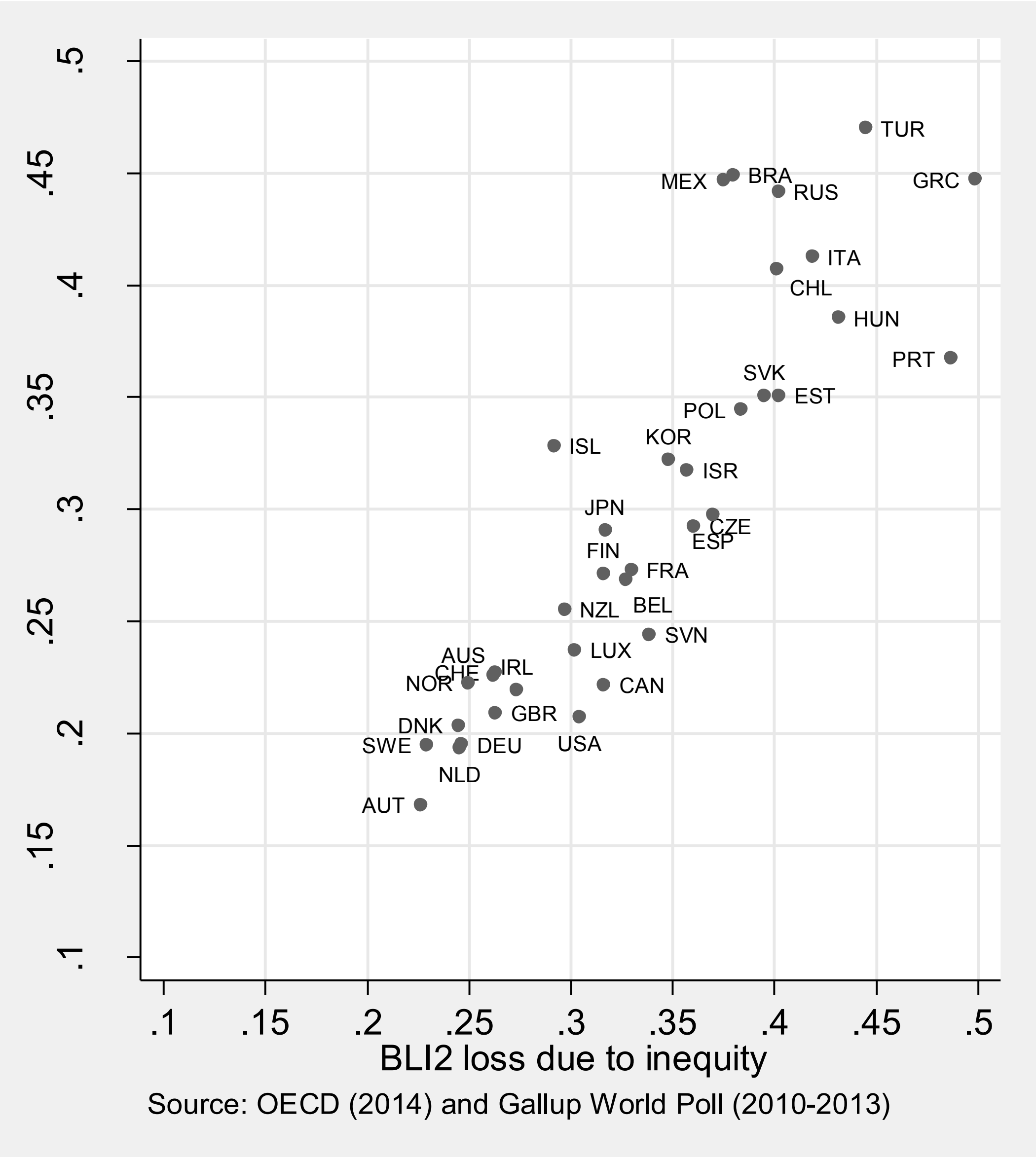


Table 7. BLI2 and potential BLI2 for the OECD member countries for two normative cases

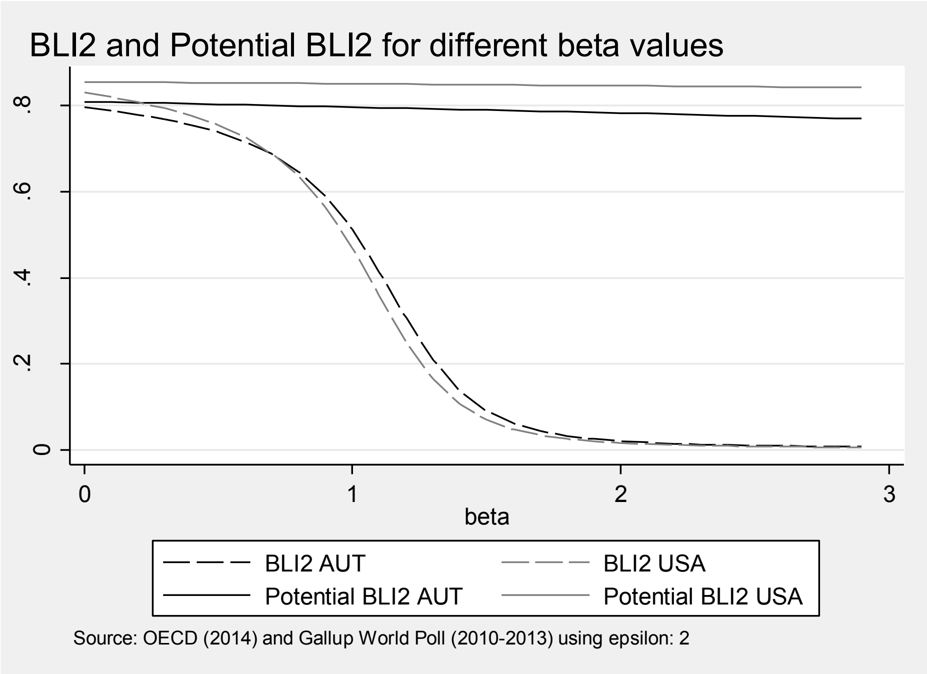
	Benchmark case (ε=2 and β=1)						Alternative case (ε=1 and β=0.5)					
Country	$BLI2$		potential $BLI2$		*Loss in $BLI2$ due to inequality*		$BLI2$		potential $BLI2$		*Loss in $BLI2$ due to inequality*	
Australia	0.469	*8*	0.821	*6*	43%	*8*	0.759	*7*	0.826	*6*	8%	*10*
Austria	0.512	*2*	0.796	*13*	36%	*1*	0.753	*9*	0.803	*11*	6%	*1*
Belgium	0.393	*16*	0.797	*12*	51%	*17*	0.721	*15*	0.801	*13*	10%	*16*
Brazil	0.205	*33*	0.601	*31*	66%	*31*	0.525	*31*	0.632	*31*	17%	*32*
Canada	0.45	*11*	0.846	*2*	47%	*13*	0.776	*4*	0.849	*2*	9%	*12*
Chile	0.213	*31*	0.599	*32*	65%	*28*	0.518	*32*	0.62	*32*	17%	*30*
Czech Republic	0.315	*21*	0.696	*23*	55%	*21*	0.632	*22*	0.712	*23*	11%	*21*
Denmark	0.49	*4*	0.815	*7*	40%	*5*	0.765	*6*	0.824	*7*	7%	*4*
Estonia	0.25	*27*	0.645	*29*	61%	*27*	0.574	*28*	0.67	*29*	14%	*27*
Finland	0.398	*15*	0.798	*11*	50%	*16*	0.726	*13*	0.808	*10*	10%	*17*
France	0.37	*18*	0.76	*18*	51%	*18*	0.687	*18*	0.765	*18*	10%	*17*
Germany	0.482	*6*	0.794	*14*	39%	*4*	0.742	*10*	0.8	*14*	7%	*5*
Greece	0.165	*35*	0.595	*34*	72%	*36*	0.496	*35*	0.611	*34*	19%	*35*
Hungary	0.224	*29*	0.641	*30*	65%	*29*	0.555	*30*	0.66	*30*	16%	*29*
Iceland	0.376	*17*	0.791	*15*	52%	*20*	0.706	*17*	0.8	*14*	12%	*22*
Ireland	0.441	*12*	0.777	*16*	43%	*10*	0.724	*14*	0.787	*16*	8%	*7*
Israel	0.305	*23*	0.696	*23*	56%	*24*	0.62	*23*	0.707	*24*	12%	*24*
Italy	0.245	*28*	0.718	*21*	66%	*32*	0.604	*24*	0.724	*20*	17%	*31*
Japan	0.348	*20*	0.719	*20*	52%	*19*	0.644	*20*	0.724	*20*	11%	*19*
Korea	0.296	*24*	0.669	*25*	56%	*23*	0.597	*25*	0.679	*26*	12%	*23*
Luxembourg	0.431	*13*	0.81	*8*	47%	*12*	0.742	*10*	0.813	*9*	9%	*13*
Mexico	0.207	*32*	0.598	*33*	65%	*30*	0.514	*33*	0.619	*33*	17%	*33*
Netherlands	0.492	*3*	0.808	*9*	39%	*3*	0.756	*8*	0.814	*8*	7%	*3*
New Zealand	0.402	*14*	0.768	*17*	48%	*14*	0.711	*16*	0.784	*17*	9%	*14*
Norway	0.484	*5*	0.83	*5*	42%	*6*	0.775	*5*	0.84	*5*	8%	*6*
Poland	0.265	*25*	0.654	*28*	60%	*25*	0.584	*27*	0.676	*27*	14%	*25*
Portugal	0.216	*30*	0.667	*26*	68%	*34*	0.569	*29*	0.676	*27*	16%	*28*
Russian Federation	0.195	*34*	0.585	*35*	67%	*33*	0.504	*34*	0.609	*35*	17%	*34*
Slovak Republic	0.26	*26*	0.661	*27*	61%	*26*	0.586	*26*	0.68	*25*	14%	*26*
Slovenia	0.367	*19*	0.735	*19*	50%	*15*	0.679	*19*	0.749	*19*	9%	*14*
Spain	0.309	*22*	0.698	*22*	56%	*22*	0.633	*21*	0.713	*22*	11%	*20*
Sweden	0.523	*1*	0.842	*3*	38%	*2*	0.79	*1*	0.848	*3*	7%	*2*
Switzerland	0.48	*7*	0.842	*3*	43%	*9*	0.777	*3*	0.846	*4*	8%	*9*
Turkey	0.154	*36*	0.522	*36*	71%	*35*	0.436	*36*	0.545	*36*	20%	*36*
United Kingdom	0.466	*10*	0.799	*10*	42%	*6*	0.74	*12*	0.803	*11*	8%	*7*
United States	0.469	*8*	0.85	*1*	45%	*11*	0.78	*2*	0.852	*1*	9%	*11*

Figure 5. The inequity and inefficiency component of multi-dimensional inequality (ε=2 and β=0)



We first look at the role of the normative parameter β. This parameter captures the degree of complementarity between the dimensions of life. Figure 6 shows the evolution for the potential $BLI2$ and $BLI2$ for Austria (in black) and the United States (in gray) for different values of β. We keep the value of ε (the degree of aversion to inequality) fixed at 2. The figure shows that the size of potential $BLI2$ depends only marginally on the parameter β. The United States scores better than Austria for the potential $BLI2$ (the full line). Indeed, also Figure 3 has shown that the United States has a higher potential $BLI2$ than Austria for the benchmark normative parameters.

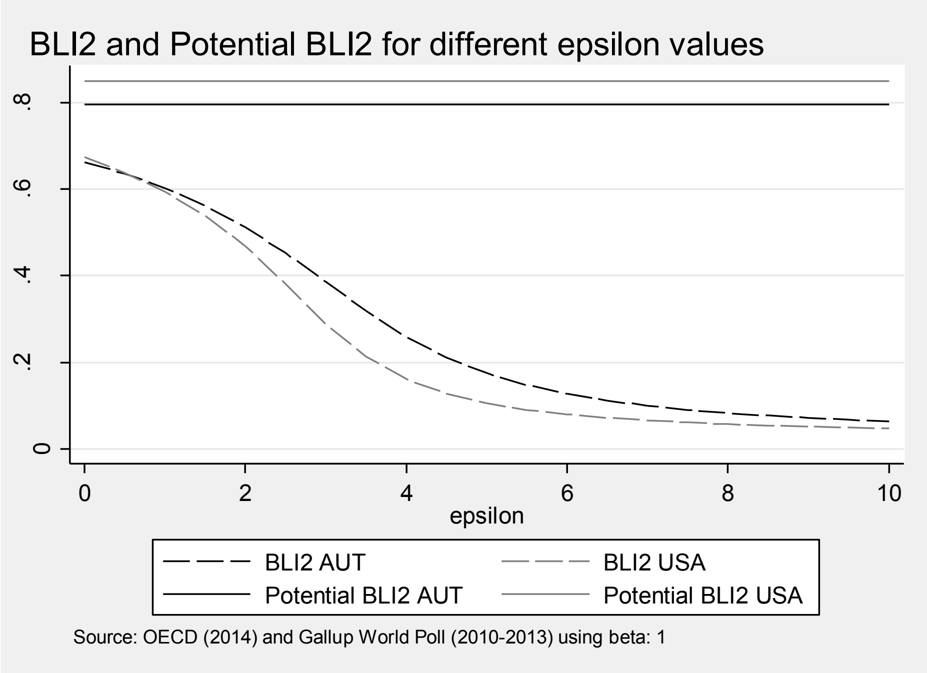
Figure 6. BLI1, potential BLI2 and BLI2 for different values of the parameter β



When looking at the $BLI2$ (the dashed lines), Figure 6 shows a large drop when the dimensions are more seen as complements (so that each country is evaluated with more attention for its worst performance). This means that the loss due to multidimensional inequality increases sharply when the normative parameter β increases. Also the ranking between the United States and Austria depends on the choice for the parameter β. For beta values close to 0 the United States has a higher $BLI2$, whereas between 0.8 and 2 Austria scores better. For higher values of β, losses due to multidimensional inequality become very large for both countries.

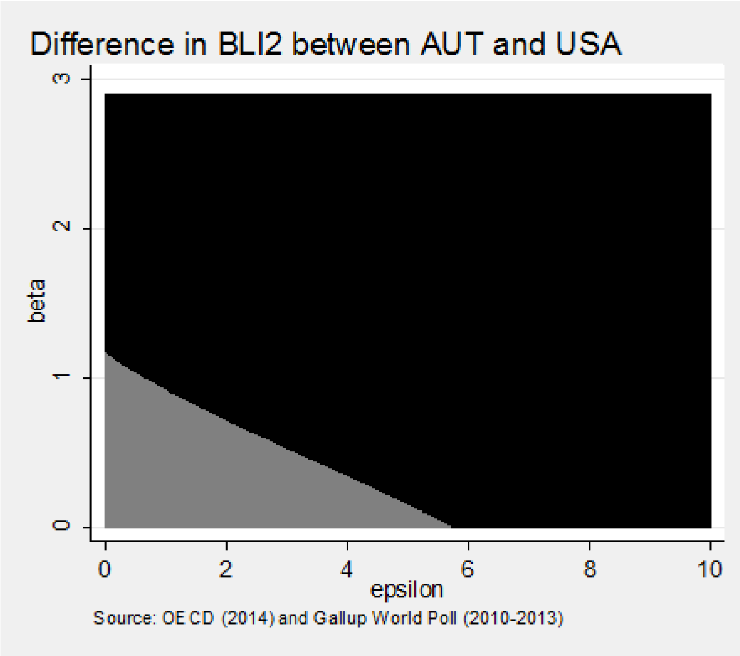
What is the role of the normative parameter ε, i.e. the inequality aversion? To analyse this, the parameter value of β is fixed at its benchmark value of 1. Figure 7 shows the evolution for the potential $BLI2$ and $BLI2$ for Austria (in black) and the United States (in gray). As can be seen from expression 6 the potential $BLI2$ does not depend on the choice of the parameter ε. The United States scores better than Austria based on these measures. The picture changes when looking at $BLI2$. In this case, the position of the United States worsens compared to Austria for larger values of ε. For values beyond 1, Austria scores better than the United States.

Figure 7. BLI1, potential BLI2 and BLI2 for different values of the parameter ε



The comparison between Austria and the United States depends on both normative parameters. Figure 8 charts how the comparison of $BLI2$ of Austria and the United States depends on the choice of the parameter values. The United States scores better in the gray area, whereas Austria scores better in the black area. Austria scores best for high values of ε and β. The more the analysis focuses on the normative space around the origin (the case reflected by the orginal $BLI1$), the more the United States outperforms Austria. The comparison of both countries depends clearly on the interplay between both parameters. By using a simplified measure that equalizes both parameters *a priori*, such as the original $BLI1$, this feature would be lost.

Figure 8. Comparison between BLI2 for Austria and the United States (United states scores better in gray area and Austria in the black area).



5 Conclusion

We can now return to the central question of this paper: are we ready to compute a distribution-sensitive *Better Life Index* for all OECD member countries? To answer this question it is useful to proceed in three steps.

First, this paper has shown how a distribution-sensitive *Better Life Index* can be designed theoretically, when a perfect data set would be available. A broad class of distribution-sensitive *Better Life Indices* that generalizes the existing *Better Life Index* and has appealing properties has been discussed. To capture different normative positions, the proposed class of indices contains three normative parameters: a weighting scheme for the dimensions; a parameter expressing the degree of complementarity between the dimensions; and the degree of inequality aversion. The resulting measures can be decomposed in their conceptual building blocks, which provides additional insights. From a theoretical perspective, the central question can be therefore answered with considerable optimism.

Of course, we do not live in a world without data constraints. Section 3 of the paper has shown that data limitations impose strong restrictions on the implementation of a distribution-sensitive *Better Life Index*. From an implementation perspective, the answer to the central question of the paper is therefore grimmer. To confront these data limitations, at least two strategies are possible. The first-best strategy is to collect better data, which is costly and labour-intense. The second-best strategy is to rely on a synthetic data set constructed by combining the available macro and micro-level information from different sources. The extent to which the results are sensitive to the assumptions implicit in the construction of such a synthetic data set is an important question for further research.

Section 4 of the paper has presented first results for a distribution-sensitive *Better Life Index* based on such a synthetic data set. This exercise revealed some interesting insights. First, Nordic countries are top-ranked according to the distribution-sensitive *Better Life Index*, while Mexico, Chile, Brazil, Greece, the Russian Federation and Turkey occupy the bottom positions. For these worse performing countries, this outcome reflects both low average scores in each of the dimensions (as captured by the original *Better Life Index*) and additionally a high level of multidimensional inequality. The sensitivity analysis has illustrated that the choice of the normative parameters on the degree of complementarity and the inequality aversion may affect the ranking of the countries. By using a measure that is insensitive to these aspects of the distribution, such as the original *Better Life Index*, this subtlety would be lost.

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APPENDIX. SUMMARY STATISTICS OF THE SYNTHETIC DATA SET

Table 8. Average score for the eleven dimensions of life based on the synthetic data

	Income and Wealth	Jobs and Earnings	Housing	Health	Work/Life Balance	Civic Engage-ment	Education and Schooling	Social Connect-ions	Environ-mental Quality	Personal Security	Subjective Well-Being
Australia	0.539	0.859	0.707	0.972	0.784	0.957	0.896	0.968	0.834	0.75	0.947
Austria	0.551	0.861	0.597	0.877	0.85	0.712	0.886	0.99	0.692	0.946	0.964
Belgium	0.647	0.788	0.688	0.897	0.938	0.674	0.884	0.947	0.701	0.792	0.914
Brazil	0.156	0.639	0.453	0.831	0.842	0.595	0.676	0.935	0.647	0.469	0.925
Canada	0.62	0.819	0.73	0.982	0.898	0.786	0.924	0.978	0.802	0.896	0.977
Chile	0.242	0.663	0.398	0.803	0.77	0.557	0.802	0.889	0.405	0.602	0.849
Czech Republic	0.286	0.691	0.529	0.804	0.884	0.612	0.938	0.903	0.739	0.714	0.861
Denmark	0.469	0.818	0.631	0.879	0.976	0.775	0.904	1	0.825	0.928	0.976
Estonia	0.211	0.62	0.446	0.751	0.922	0.482	0.935	0.926	0.812	0.751	0.69
Finland	0.416	0.777	0.633	0.873	0.921	0.761	0.955	0.972	0.825	0.914	0.957
France	0.55	0.717	0.637	0.874	0.877	0.583	0.84	0.947	0.806	0.773	0.857
Germany	0.575	0.831	0.63	0.85	0.912	0.579	0.928	0.968	0.815	0.878	0.896
Greece	0.294	0.367	0.481	0.915	0.899	0.618	0.839	0.712	0.544	0.574	0.607
Hungary	0.244	0.59	0.439	0.766	0.935	0.687	0.886	0.91	0.731	0.642	0.632
Iceland	0.446	0.842	0.612	0.932	0.796	0.66	0.878	1	0.81	0.948	0.965
Ireland	0.406	0.666	0.699	0.953	0.925	0.767	0.874	0.996	0.792	0.811	0.869
Israel	0.468	0.726	0.476	0.949	0.734	0.472	0.852	0.934	0.606	0.705	0.914
Italy	0.517	0.657	0.557	0.861	0.924	0.621	0.788	0.953	0.686	0.714	0.773
Japan	0.638	0.816	0.496	0.667	0.703	0.633	0.935	0.941	0.679	0.782	0.768
Korea	0.335	0.814	0.572	0.695	0.642	0.858	0.919	0.802	0.571	0.657	0.772
Luxembourg	0.666	0.864	0.629	0.895	0.934	0.749	0.814	0.922	0.778	0.858	0.917
Mexico	0.202	0.691	0.44	0.815	0.6	0.73	0.642	0.77	0.528	0.587	0.957
Netherlands	0.593	0.861	0.677	0.918	0.974	0.666	0.891	0.959	0.656	0.896	0.952
New Zealand	0.304	0.772	0.657	0.989	0.812	0.844	0.883	1	0.84	0.753	0.936
Norway	0.437	0.906	0.719	0.901	0.949	0.773	0.899	0.969	0.817	1	0.987
Poland	0.244	0.619	0.436	0.787	0.854	0.764	0.946	0.934	0.537	0.793	0.739
Portugal	0.349	0.539	0.643	0.766	0.858	0.594	0.726	0.891	0.749	0.748	0.663
Russian Federation	0.23	0.727	0.319	0.624	0.964	0.459	0.897	0.878	0.568	0.524	0.712
Slovak Republic	0.254	0.543	0.489	0.814	0.892	0.605	0.891	0.922	0.783	0.664	0.763
Slovenia	0.32	0.708	0.602	0.822	0.889	0.797	0.916	0.967	0.682	0.947	0.768
Spain	0.378	0.392	0.668	0.918	0.931	0.685	0.79	0.961	0.63	0.838	0.791
Sweden	0.557	0.792	0.634	0.941	0.957	0.927	0.929	0.948	0.885	0.921	0.956
Switzerland	0.768	0.923	0.637	0.954	0.882	0.627	0.912	0.986	0.77	0.902	1
Turkey	0.187	0.582	0.275	0.826	0.418	0.709	0.669	0.822	0.427	0.651	0.629
United Kingdom	0.553	0.781	0.621	0.923	0.82	0.853	0.862	0.977	0.834	0.825	0.89
United States	1	0.829	0.735	0.975	0.812	0.716	0.909	0.942	0.756	0.861	0.904

Table 9. Gini coefficients for the eight non-equal dimensions of life based on the synthetic data

	Income and Wealth	Jobs and Earnings	Health	Education and Schooling	Social Connect-ions	Environ-mental Quality	Personal Security	Subjective Well-Being
Australia	0.324	0.106	0.19	0.178	0.0513	0.0757	0.395	0.126
Austria	0.282	0.0815	0.168	0.163	0.0547	0.0746	0.185	0.13
Belgium	0.269	0.0916	0.234	0.263	0.0769	0.19	0.345	0.121
Brazil	0.469	0.117	0.201	0.513	0.0913	0.24	0.617	0.168
Canada	0.316	0.103	0.198	0.294	0.0623	0.118	0.257	0.122
Chile	0.503	0.121	0.242	0.403	0.166	0.242	0.495	0.18
Czech Republic	0.256	0.0943	0.23	0.224	0.0931	0.188	0.419	0.169
Denmark	0.253	0.118	0.26	0.155	0.0411	0.0595	0.218	0.107
Estonia	0.323	0.0889	0.305	0.378	0.0965	0.215	0.379	0.194
Finland	0.261	0.0873	0.229	0.396	0.0618	0.0765	0.237	0.113
France	0.309	0.0991	0.155	0.315	0.0772	0.188	0.367	0.141
Germany	0.293	0.0886	0.22	0.168	0.0601	0.0729	0.269	0.145
Greece	0.336	0.246	0.2	0.433	0.197	0.28	0.534	0.25
Hungary	0.29	0.108	0.305	0.417	0.106	0.19	0.481	0.244
Iceland	0.251	0.0745	0.19	0.611	0.0279	0.0541	0.192	0.107
Ireland	0.3	0.152	0.138	0.231	0.0352	0.0913	0.333	0.146
Israel	0.377	0.093	0.22	0.212	0.11	0.345	0.398	0.126
Italy	0.322	0.134	0.146	0.622	0.109	0.261	0.427	0.164
Japan	0.336	0.0893	0.199	0.349	0.112	0.148	0.356	0.175
Korea	0.307	0.112	0.229	0.264	0.179	0.208	0.472	0.173
Luxembourg	0.276	0.0823	0.171	0.299	0.0871	0.123	0.284	0.124
Mexico	0.482	0.132	0.174	0.523	0.194	0.23	0.488	0.166
Netherlands	0.278	0.106	0.209	0.199	0.0665	0.11	0.259	0.0886
New Zealand	0.323	0.126	0.174	0.277	0.0519	0.0863	0.404	0.126
Norway	0.25	0.0991	0.249	0.303	0.0486	0.0446	0.144	0.118
Poland	0.304	0.106	0.294	0.358	0.0719	0.204	0.329	0.183
Portugal	0.341	0.106	0.245	0.504	0.141	0.117	0.387	0.239
Russian Federation	0.356	0.0754	0.359	0.298	0.104	0.434	0.573	0.199
Slovak Republic	0.262	0.112	0.266	0.321	0.082	0.2	0.46	0.178
Slovenia	0.245	0.0916	0.255	0.229	0.0745	0.151	0.199	0.197
Spain	0.344	0.207	0.159	0.315	0.0595	0.176	0.293	0.176
Sweden	0.273	0.0968	0.209	0.213	0.0653	0.0616	0.232	0.116
Switzerland	0.289	0.0773	0.175	0.311	0.0524	0.0861	0.248	0.103
Turkey	0.412	0.136	0.198	0.55	0.248	0.336	0.446	0.228
United Kingdom	0.344	0.118	0.174	0.209	0.0576	0.0725	0.306	0.149
United States	0.389	0.152	0.188	0.181	0.0785	0.122	0.286	0.16