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Human Development, Inequality, and Poverty: Empirical Findings

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Abstract
This paper is devoted to the discussion of empirical findings related to research on the measurement of human development, inequality, and poverty. It is divided into three main sections. In the first of these three sections, we discuss some practical concerns raised about the Human Development Index and how these concerns have been empirically addressed. In the second of these sections, we discuss various empirical studies and findings relating to the level of human development and the level of inequality in human development. Finally, we discuss the empirical research and findings relating to multidimensional poverty.

Keywords: Human Development Index, Inequality-adjusted Human Development Index, Multidimensional Poverty Index

JEL classification: O15, D63, I32

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1. Introduction

The concept of human development, which is a process of enlarging people's choices, is a broad concept and inherently multidimensional. It is already well established that we cannot obtain a comprehensive picture of human development by merely looking at the performance of any single dimension such as income. This is so because not all variables that affect human development evolve similarly. **Table 1** presents illustrations of certain countries from the 1990 Human Development Report (HDR) that show mismatches between performances in monetary and non-monetary dimensions. The first set of three countries – Sri Lanka, Jamaica, and Costa Rica – had high life expectancy and adult literacy rates and low infant mortality rates despite low levels of per-capita Gross National Product (GNP). In contrast, the second set of three countries – Brazil, Oman, and Saudi Arabia – had much lower life expectancy and adult literacy rates and higher infant mortality rates despite much higher levels of per-capita GNP.

Table 1: The Gross National Product vs. Other Social Indicators

Country	GNP Per Capita (USD)	Life Expectancy (Years)	Adult Literacy Rate (%)	Infant Mortality (Per 1,000 Live Births)
Modest GNP per capita with high human development				
Sri Lanka	400	71	87	32
Jamaica	940	74	82	18
Costa Rica	1,610	75	93	18
High GNP per capita with modest human development				
Brazil	2,020	65	78	62
Oman	5,810	57	30	40
Saudi Arabia	6,200	64	55	70

Source: Table 1.1 of *Human Development Report* (1990)

The lack of perfect synergies between monetary and non-monetary dimensions has shifted the focus from a merely economic growth led development process to a more holistic process of development that focuses on monetary as well as non-monetary dimensions. This more holistic process of development calls for a multidimensional approach to measurement. It should be borne in mind that the objective of measurement exercises is to capture and reflect various aspects of human development that assist in guiding better policies towards improving human lives. It is thus crucial that these measurement exercises are technically sound yet are amenable to practical issues and policy guidance at the same time.

There may be two distinct ways to assess progress when multiple dimensions are involved. One is to look at progress in different dimensions separately and the other is to aggregate performance into a single index to assess overall progress. One can find good arguments in favour of each of those mechanisms.

There are two key arguments for looking at performance in different dimensions separately. One is that it avoids the loss of information that occurs when we aggregate performance in different dimensions into a single index. The other is that it does not require making difficult decisions regarding the relative importance of the different dimensions and the suitability of various aggregation procedures. We also find good reasons to favour a synthetic measure. First, a single index summarizing overall performance may send a more powerful message than a dashboard of large number of isolated indices (Stiglitz, Sen, and Fitoussi 2009). This is the reason why the GNP/GDP and the Human Development Index (HDI) have become more popular and have played a more effective role in policy design than the dashboard of Millennium Development Goals indicators (see section 4). Second, a single real-valued index satisfies **completeness** and **transitivity**. The first property permits full comparability whereas the second ensures consistent evaluations. Third, looking at different dimensions separately implies ignoring the joint distribution of achievements across the population. We discuss this issue in detail later on.

The HDI is one of the social indices, introduced in various Human Development Reports in the past two decades, with the objective of creating a family of rich and highly informative indices to assess the degree of development in a large number of countries. Those indicators are aimed at answering a basic question: How have countries progressed in terms of human development over the past decades? The data using the new HDI, introduced in the 2010 HDR, show a relevant worldwide improvement in the level of human development for the period 1980–2013 in all dimensions, even though the rate of improvement varies in different periods. Table 2 provides a summary of the evolution in global human development by groups of countries, according to their level of human development. Countries experiencing larger increases in the HDI are the medium or low human development countries.

Table 2: The Growth of HDI in the World (1980–2013) by Groups of Countries

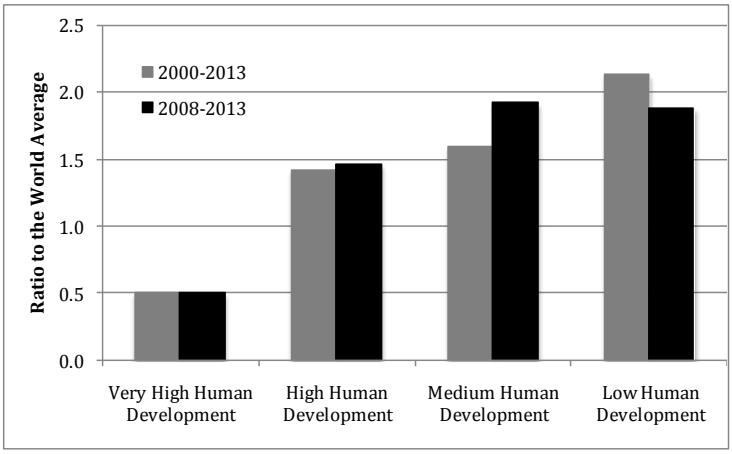
	Average Annual HDI Growth				
	1980–2013	**1980–1990**	**1990–2000**	**2000–2013**	**2008–2013**
Very high human development	0.53	0.52	0.62	0.37	0.20
High human development	1.14	1.04	0.81	1.04	0.60
Medium human development	1.41	1.22	1.09	1.17	0.79
Low human development	1.31	0.64	0.95	1.56	0.77
World	**0.77**	**0.66**	**0.67**	**0.73**	**0.41**

Source: *HDR 2014*

The average yearly HDI growth rate for the period 1980–2013 in the world is 0.77%, with values of 0.53% for the most developed countries and 1.31% for the less developed ones. Notice that the period 2000–2013 shows larger differences in favour of those countries with low human development, which conveys a rather positive message. The 2008 crisis clearly affected the evolution of human development by reducing the annual rates of growth, as shown in the last column of Table 2. Yet it might be worth

noting that the slowdown is mostly a scale effect, as the shares in average growth have remained quite stable, as Figure 1 shows. The vertical axis measures the ratio of the average annual HDI growth in different HDI categories to the overall average annual HDI growth, which is directly computed using the numbers in Table 2. For example, the ratio of the average annual HDI growth of very high human development countries to the world average for the period 2000–2013 is computed as 0.37/0.73 = 0.5, which is the height of the corresponding grey bar in Figure 1.

Figure 1: The Ratio of Regional Growth to Overall Growth in HDI



The rest of this paper is structured as follows. In section 2, we discuss certain practical concerns about the HDI and how they have been empirically addressed. In section 3, we discuss various inequality-adjusted human development indices and explore the relationship between the level of human development and the level of inequality. In section 4, we discuss the empirical studies relating to the poverty indices reported in Human Development Reports.

2. Practical Concerns about the HDI

The country rankings generated by the HDI have received a large amount of global attention. A number of practical issues, however, have raised concerns over the application of the index. The first issue that has received a great deal of attention is the choice of equal weights for each of the three dimensions (Kelley 1991; Desai 1991). It has been argued that the equal weight structure entails a very strong value judgment. Rankings or comparisons may alter if an alternative weighting structure entailing a different value judgment is selected. This concern has been well-spotted and various data-driven techniques, such as principal component analysis (UNDP 1993; Noorbakhsh 1998; Nguefack-Tsague et al. 2011) and data envelopment analysis (Mahlberg and Obersteiner 2001; Despotis 2005), have been used to devise alternative weighting structures. Some of these applications have agreed with the equal weight structure and some have disagreed. An interesting study was pursued by Chaudhury and Squire (2006), who conducted an opinion survey among experts from different countries. Their study found experts somewhat agreed with the equal weight structure of the HDI.

Whichever way the weighting structure is determined, there is always some degree of arbitrariness in the choice and so another branch of literature has taken an alternative route. Instead of developing a new technique for weighting dimensions, these studies have proposed conducting sensitivity analysis (Saisana et al. 2005) and robustness tests (Cherchye et al. 2008; Foster et al. 2009; Permanyer 2011) with respect to the choice of initial weights. These robustness and sensitivity analyses test whether or not a given pair-wise comparison is fully robust to alternative weighting structures and if the comparison is not fully robust then to what extent the comparison is robust. Foster et al. (2009) found that nearly 70% of all pair-wise HDI comparisons for various years were fully robust. This implies that no matter how the initial equal weighting structure is altered, 70% of all pair-wise comparisons would not change.[1] When the initial equal weights were allowed to vary by 25% in any direction, then nearly 92% of pair-wise HDI comparisons were robust. Thus, although there has been a strong animosity against the choice of equal weights, empirical findings tend to agree with this choice (even when there may be particular cases where the directions of pair-wise comparisons alter).

The issue of robustness with respect to the choice of weights is in fact linked to a second issue related to the correlation or statistical association between the component dimensions. If the statistical associations between component dimensions are high, then any debate over the choice of weights loses most of its significance. Cahill (2005) used six alternative weighting structures to compute the HDI ranking using the three highly correlated dimensions of HDI and found HDI rankings across countries to be very highly correlated to each other. In fact, in a hypothetical world, if all three dimensions of the HDI were perfectly positively associated, then any two alternative weighting structures would agree over every pair-wise comparison (Foster, McGillivray, and Seth 2013). If an overall index provides similar rankings to any of its component indices, then what additional information does the aggregate index provide? This was precisely the point made by McGillivray (1991). The Spearman's rank correlation coefficients between the three dimensions as well as the rank correlation between the HDI and its component dimensions appeared to be very high (ranging between 0.74 and 0.97 using the data from 1990 Human Development Report). McGillivray and White (1993) also found a very high correlation between HDI rankings and the rankings based on per-capita GNP that the HDI was trying to replace. This type of high association between HDI rankings and rankings according to its component dimensions, as well as the high association between HDI rankings and per-capita GNP rankings, may mean that the HDI is a redundant index (McGillivray 1991).

This way of understanding redundancy of an index however can be debated. First, note that the even though the rank correlation coefficients were high when they were computed across all countries, they were not necessarily high across subgroups of countries. For example, the rank correlation coefficients ranged between –0.14 and 0.4 when McGillivray (1991) considered only the low human development countries. Put differently, a high rank correlation between two long lists of country outcomes is perfectly

[1] How many pair-wise comparisons are there? If there are 100 countries, then the number of total possible pair-wise comparisons is $100 \times 99/2 = 4950$.

compatible with very large differences between individual realizations. Second, the high statistical associations existed at the aggregate level across countries. This may not necessarily imply that such high associations exist between dimensions at more disaggregated levels – across states/provinces, across municipalities or across households. Therefore, a deeper analysis and understanding of the redundancy aspect of an index is required.

A third issue that is often raised relates to the particular functional form used for aggregating the dimensional performances. Note that the tradition HDI until 2009 is obtained by linearly aggregating the performance in three dimensions, which also assumed a strong value judgment. Besides, linear aggregation has a number of drawbacks. It implies assuming perfect substitutability between the components values, i.e., it amounts to admitting that we can substitute, for instance, expected life years by education at a constant rate, no matter the average level of health (see Ravallion 2010 for a discussion on trade-offs between dimensions). In addition, an additive index generates a ranking that is sensitive to the normalization of the different dimensions, where a change in the arbitrary normalization of the underlying variable induces changes in rankings. To counter these limitations of the linear HDI, the 2010 HDR introduced a new aggregation formulation based on the geometric mean as discussed in Seth and Villar (2017). The country rankings produced by the new HDI was not found to be strikingly different from the rankings produced by the linear HDI using the 2010 country data (UNDP 2010, p. 227).

The geometric mean is a well-known aggregator in economics, corresponding to the familiar symmetric Cobb-Douglas formula for production and utility functions and exhibits much better properties regarding substitutability among the dimensions. However, the benefit of using the geometric formulation may not be fully enjoyed unless appropriate normalizations of the original underlying variables are undertaken. The country rankings are still sensitive to the selection of the minimum values for normalization. For the construction of the HDI, the normalized values of each dimension is obtained by subtracting the minimum value from the original variable in each dimension and then divided by the difference of the maximum and the minimum values. Any change in the minimum values still alters country rankings. One way of addressing this problem is to set the minimum values equal to zero and then to normalize each dimension by dividing the related variable by the corresponding maximum value only (Herrero, Martínez, and Villar 2010; Alkire and Foster 2010).

All the relevant practical issues involving the measurement of human development are very important but ignore one key practical issue, which is the consideration of distributional aspects. The discussion until now assumes that dimensional indices are first somehow obtained and then meaningfully aggregated to produce the index. By doing this, dimensional indices and thus the HDI ignore the existing inequality in human development. In the next section, we discuss how distribution concerns have been incorporated into the measurement of human development.

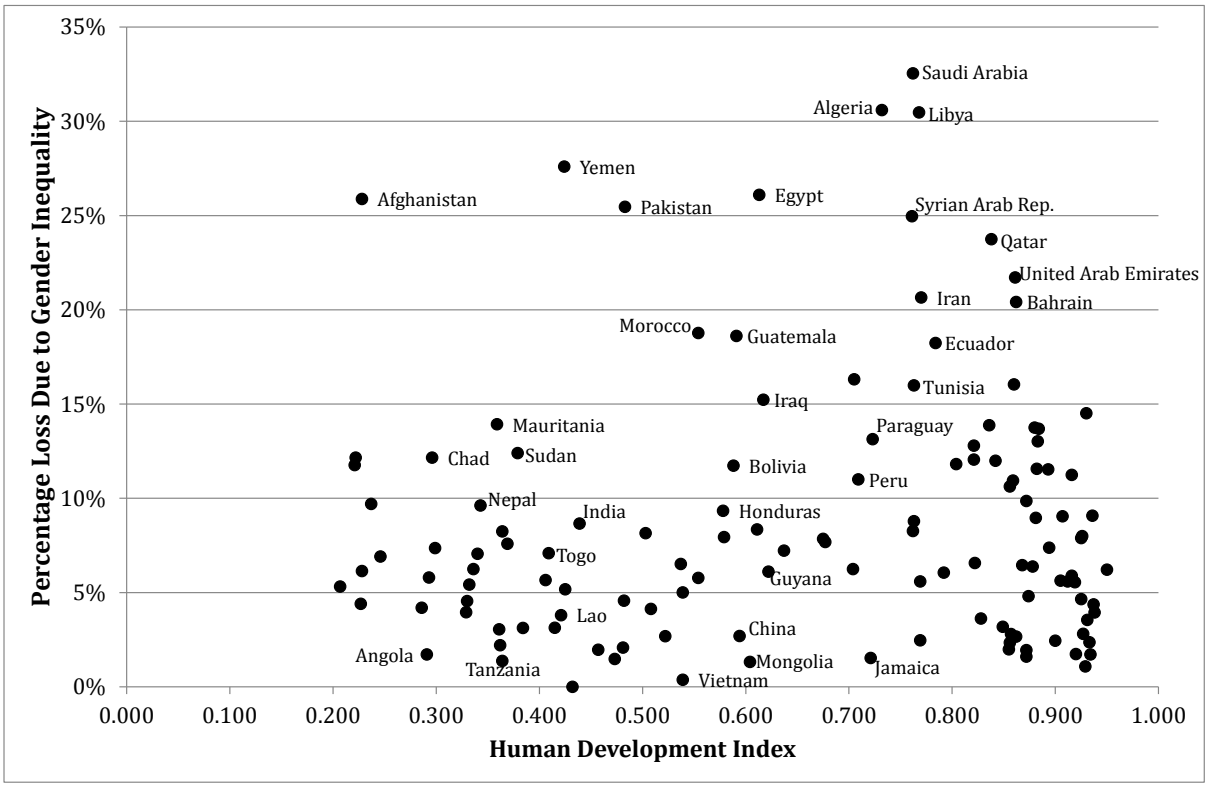
3. Distributional Concerns While Measuring Human Development

The first attempt to incorporate the distributional aspects into the measurement of human development was made by Anand and Sen (1995) who captured inequality across gender in the same three dimensions of the HDI. The index, well known as the Gender-related Development Index (GDI), is based on equally distributed equivalent achievements (Atkinson 1970), which is equivalent to the generalized means with a particular restriction on the relevant parameter. The generalized mean of order α of a vector $y = (y_1, \dots, y_n)$ with n positive achievements is defined as

$$\mu_\alpha(y) = \begin{cases} \left[\frac{1}{n}\sum_{i=1}^{n} y_i^\alpha\right]^{1/\alpha} & \text{for } \alpha \neq 0 \\ \left[\prod_{i=1}^{n} y_i\right]^{1/n} & \text{for } \alpha = 0 \end{cases}.$$

The parameter α is an inequality aversion parameter. When $\alpha = 1$, then $\mu_1(y)$ is the average of all achievements in y without any consideration of inequality between the n elements. However, when $\alpha < 1$, then $\mu_\alpha(y)$ is the equally distributed equivalent achievement of y, which implies that $\mu_\alpha(y)$ would yield the same level of overall achievement if each of the n achievements were equal to $\mu_\alpha(y)$. The higher the aversion to inequality (smaller the value of α) is, the lower the value of $\mu_\alpha(y)$ is.

Figure 2: HDI and Loss Due to Gender Inequality across 130 Countries in 1992



Source: Computation used data from Tables 1.1, 1.2, and 3.1 of *Human Development Report 1995*.

The GDI is computed in two steps. First, an equally distributed equivalent achievement for each of the three dimensions is calculated using the male and female achievements. Then, in the second step, the GDI of a country is computed as a simple average of the three equally distributed equivalent achievements. The GDI can be seen as a gender-inequality adjusted Human Development Index. The loss in human development due to gender inequality can be computed as (HDI – GDI)/HDI.

Figure 2 presents a scatter-plot showing the relation between HDI levels (horizontal axis) and percentage losses in human development due to inequality between gender (vertical axis) across 130 countries for year 1992. There does not appear to be any relationship between the HDI levels and losses in human development due to gender inequality. Thus, it cannot be claimed that countries with lower human development have larger gender disparities. In fact, certain high-medium HDI countries, such as Saudi Arabia and Algeria, appear to have had high levels of gender inequality. Whereas, certain low human development countries, such as Angola and Tanzania, appear to have had very low levels of gender inequality.

Gender inequality only captures inequality between two genders but ignores inequality within groups. Even when human development levels are less unequal across genders, large inequalities may exist across the population. An attempt to incorporate distributional aspects using a much wider perspective was made by Hicks (1997). In order to capture inequality, Hicks computed a Gini coefficient for income distribution, educational distribution, and longevity distribution as follows. The Gini coefficient for income distribution is computed using the data on income shares by quintile. In other words, the Gini coefficient is computed from certain discrete points from the Lorenz curves. The Gini coefficient of the education distribution is also computed from certain discrete data points by classifying the education data into six categories: no education, some primary education, completed primary education, some secondary education, completed secondary education, and some higher education. Finally, the Gini coefficient of the longevity distribution is obtained from mortality statistics (death rates) that were available across age, gender, and rural/urban residence for nine consecutive years.

Then the inequality-adjusted index for each dimension is computed by multiplying the dimensional achievement by a factor that is inversely related to the corresponding Gini coefficient. Let us denote the original dimensional achievements of the three dimensions of the HDI by x_1, x_2, and x_3 and the corresponding dimensional Gini coefficients by G_1, G_2, and G_3. The inequality-adjusted index of dimension i is computed as $x_i \times (1 - G_i)$. The Inequality-Adjusted HDI, referred to by Hicks as the IAHDI, is a simple average of the three dimensional inequality-adjusted indices such that

$$\text{IAHDI} = \frac{1}{3}\sum_{i=1}^{3} x_i \times (1 - G_i).$$

Note that in an ideal situation where there is no inequality across the categories, each inequality-adjusted dimensional index is equal to the corresponding dimensional achievement and the IAHDI is equal to the

HDI. On the other hand, if inequality in each dimension increases but the average achievement remains the same, IAHDI falls discounting for the higher inequality.

Hicks applied the index to 20 developing countries using HDI data for year 1995 and showed how the country rankings changed when the HDI was adjusted for existing inequality (see Table 4 of Hicks 1997). For example, Costa Rica and the Republic of Korea had the same level of HDI of 0.883 and 0.882, respectively, in 1995. However, the levels of inequality in all three dimensions were higher in Costa Rica than that in the Republic of Korea. As a result, the IAHDI of Costa Rica was much lower (0.561) than that of the Republic of Korea (0.621). Using HDI and IAHDI values, Hicks computed the percentage loss in the level of wellbeing due to existing inequality in the three dimensions by (HDI – IAHDI)/HDI. The percentage loss ranged from 29.6% for the Republic of Korea to 56.6% for Guatemala and Bangladesh.

Another attempt to incorporate distributional concerns into the measurement of the HDI was made by Foster, Lopez-Calva, and Szekely (2005). Instead of the Gini coefficient to capture inequality across each distribution, they propose a framework based on generalized means. A simple average or arithmetic mean of all elements in y can be obtained by setting $\alpha = 1$, which we denote as μ. The Atkinson measure of inequality of order α can be defined as $I_\alpha = (\mu - \mu_\alpha)/\mu$ for $\alpha < 1$. This relationship can be expressed as $\mu_\alpha = \mu(1 - I_\alpha)$. Foster, Lopez-Calva, and Szekely first propose computing the general mean of order α for each distribution: income, education, and health, where inequality within each distribution is captured through the Atkinson measure of inequality. In the second stage, the three dimensional general means are again aggregated using a general mean of order α to obtain the inequality-adjusted HDI. Note the generalized means capture inequality within the distributions during the first stage and the second stage generalized mean ensures that the overall index is discounted or reduced if the performance in three dimensions is not uniform.

The authors apply the family of inequality-adjusted HDI to a data sample from the 2000 Mexican Population Census. The sample contained 10,099,182 individual records from 2.2 million households, each with information on income and education. However, the Population Census did not include any information on health and so individual-level health information was imputed from municipality-level data, which ensured that inequalities in health across households living in different areas are still captured.

In order to make this human development index as comparable as possible with the traditional HDI, certain adjustments are made to the variables. As income is only one component of Gross Domestic Product, adjustments are made to household income. Two variables are used to capture the education status of the sample households, as in the traditional HDI. One is the literacy variable, which is computed as the proportion of literate individuals over 14 years of age to the total number of individuals older than 14. The other is the attendance variable, which is the proportion of 6-year-old to 24-year-old individuals attending school. As in the traditional HDI, the education index for each individual is

constructed by giving a two-third weight to the literacy variable and a one-third weight to the attendance variable. However, the health indicator is slightly different, using infant mortality or infant survival rates as proxies for the health conditions. Note that this variable is available only at the municipality level and not at the household level and so inequality across health is only captured at the municipality level.

They compute the HDIs ($\alpha = 1$) and inequality-adjusted HDIs ($\alpha = -2$) nationally and for all 32 states of Mexico (see Table 1 of Foster, Lopez-Calva, and Szekely 2005). The loss of wellbeing due to inequality is computed as (HDI – IAHDI)/HDI. At the national level, the loss in wellbeing due to inequality appears to be 26%. However, the loss in wellbeing varies widely from state to state: from nearly 14% in Distrito Federal and Baja California to 38% in the state of Oaxaca. The losses in wellbeing in the states of Chiapas, Guerrero, and Zacatecas are more than 30%. The use of an inequality-adjusted HDI causes the ranks of the states to change markedly.

A particular measure from the Foster et al. (2005) family of measures has been used by Alkire and Foster (2010), who propose using the measure for $\alpha = 0$ (geometric mean), which satisfies certain interesting and policy-relevant properties. Note that meaningful comparison of the HDI that is based on the geometric mean (i.e., the new HDI formulation introduced in the 2010 HDR that replaced the traditional linear formulation of the HDI) and the inequality-adjusted HDI proposed by Alkire and Foster (2010) requires that no logarithmic transformation is applied to the income variable. If a logarithmic transformation is applied, then there would be an excess emphasis on income inequality because a logarithmic transformation is already a concave transformation.

Table 3: Inequality and Human Development

	HDI	Inequality-adjusted HDI (IHDI)	Overall loss (%)
Very high human development	0.890	0.780	12.3
High human development	0.735	0.590	19.7
Medium human development	0.614	0.457	25.6
Low human development	0.493	0.332	32.6

Source: *Human Development Report* 2014

The data referring to the inequality-adjusted HDI reveal two key messages. First, inequality-adjusted values may change the ranking of individual countries considerably, no matter the level of development (see the Appendix). Second, the overall loss due to inequality is, on average, inversely proportional to the degree of development (we shall come back to this point later on).

A somewhat different approach to reflect inequality in the level of human development has been followed by Grimm et al. (2008) who computed HDIs for different income groups. Grimm et al. apply their approach to 13 developing countries, where each country has a household income survey and a Demographic Health Survey (DHS). The household income survey is used to compute the indices for education and income, and the DHS is used to compute the life expectancy indices.

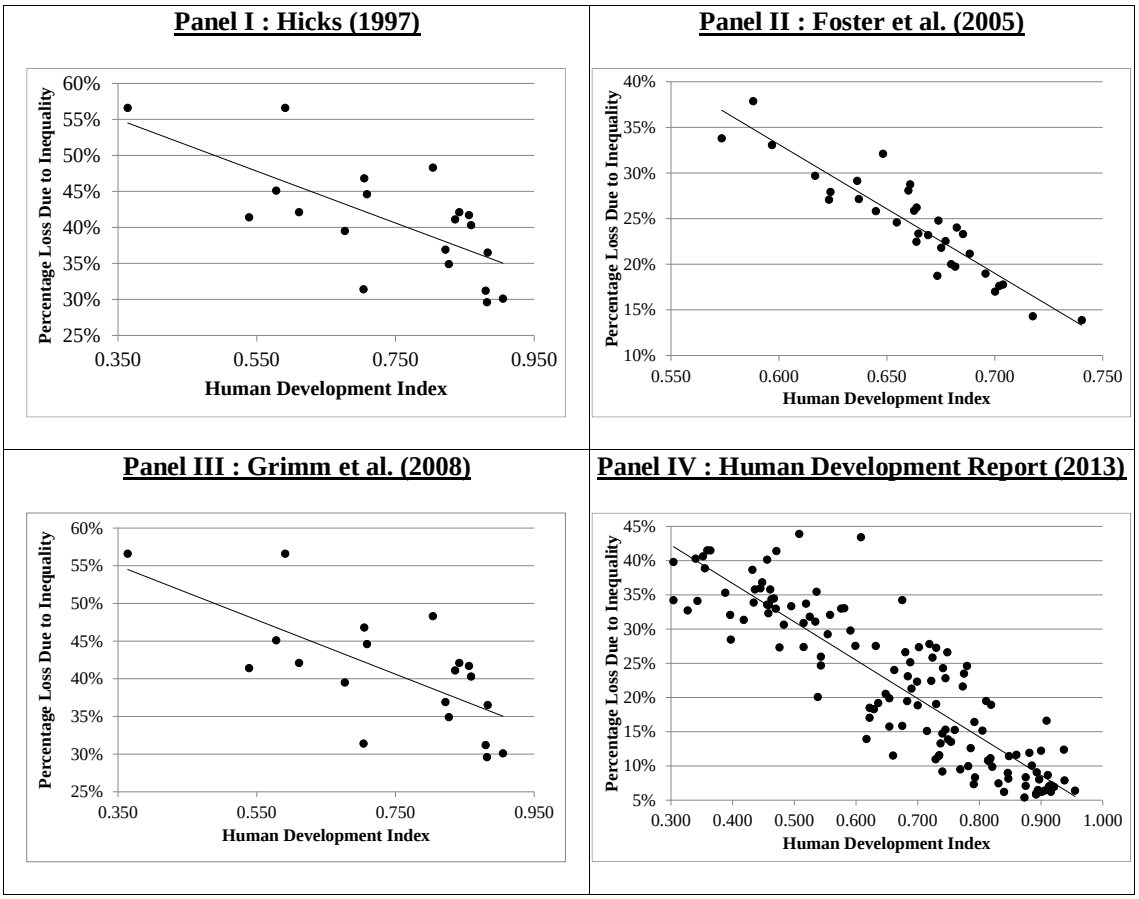
In order to compute the quintile-based indices, it is important to match the quintiles across two surveys for each country. Grimm et al. propose two alternative approaches for this purpose. One is a regression-based method where one first needs to identify a common set of variables in both surveys that correlate with the income variable in the income survey. The set of variables should include some characteristics of household heads, some characteristics of households, and some information on housing conditions. Income is then regressed on the set of common variables from the income survey and the regression coefficients are used to predict household incomes in the DHS, which are used to construct the cumulative distribution of income and thus the income quintiles. The other approach is to use principal component analysis to construct the cumulative distribution of the asset index and then the asset quintiles. In this alternative approach, it is assumed that the asset quintiles yield a classification that is consistent with what is obtained by observed income in the respective income surveys.

Once the quintiles are classified, the dimensional indices of income and education indices are constructed from the income surveys and the health indices are constructed from the health surveys. The HDIs from the dimensional indices are constructed using a weighted average, where the weight structure is the same as that of the traditional HDI.

In order to reflect inequality in the HDIs, the authors compute the ratio of HDI between the richest and the poorest quintile. Their results reveal stark differences across countries. They analysed the data for 13 developing countries and two industrialized countries (see Table 1 of Grimm et al. 2008). The 13 developing countries are Bolivia, Burkina Faso, Cameroon, Columbia, Cote d'Ivoire, Guinea, Indonesia, Madagascar, Mozambique, Nicaragua, South Africa, Vietnam, and Zambia. Of these 13 countries, the high inequality countries are Guinea, Burkina Faso, Zambia, and Madagascar, where the HDI for the richest income quintile is 1.7 times or higher than the poorest quintile. For the second group of countries – Bolivia, Cameroon, Nicaragua, Cote d'Ivoire, Mozambique, and South Africa – the ratios of the richest to the poorest range between 1.5 and 1.7. For the third group of countries, consisting of Colombia, Vietnam, and Indonesia, the ratio of the HDI for the richest to the poorest quintile is smaller but still ranges between 1.3 and 1.5.

One consistent aspect of all these studies is that the level of human development is inversely related to the level of inequality in human development, both across countries and within countries. In **Figure 3**, we present four diagrams in four panels. In each diagram, the level of human development is presented on the horizontal axis and the level of inequality on the vertical axis. Panel I presents the relationship across 20 developing countries as computed by Hicks (1997). Panel II presents the relationship across 32 Mexican states as computed by Foster et al. (2005). Panel III presents the relationship across 13 developing countries as computed by Grimm et al. (2008). Finally, Panel IV presents the relationship between HDI and the percentage loss in human development due to inequality using the inequality-adjusted HDI across 132 countries reported in the 2013 Human Development Report. It is evident that the data from each of these four sources demonstrate a strong negative relationship between the level of HDI and inequality in human development.

Figure 3: Comparison of the HDI Level and Inequality in Human Development



Sensitivity to Joint Distribution

Unlike in the single dimensional context, analysis in the multidimensional context entails two distinct forms of inequality. The first pertains to the spread of the distribution across persons, analogous to unidimensional inequality. The second, in contrast, deals with the joint distribution among dimensions. This second form of inequality is important because a change in the joint distribution may alter individual- level evaluations as well as overall inequality. Let us look at the following example of two achievement matrices, where rows denote persons and columns denote dimensions.

Achievement Matrix I

$$\begin{bmatrix} 0.90 & 0.90 & 0.90 \\ 0.30 & 0.80 & 0.80 \\ 0.30 & 0.40 & 0.40 \end{bmatrix}$$

Achievement Matrix II

$$\begin{bmatrix} 0.90 & 0.90 & 0.90 \\ 0.30 & 0.40 & 0.80 \\ 0.30 & 0.80 & 0.40 \end{bmatrix}$$

It is evident from Achievement Matrix I that person 1 has higher levels of achievement in all three dimensions. Person 2 has higher achievement in the second and third dimensions than that of Person 3, but enjoys the same level of achievement in the first dimension. If we look at the distribution of achievements in each of the three dimensions in Achievement Matrix II, it is clear that each dimensional distribution is identical to the corresponding dimensional distribution in Achievement Matrix I. In other

words, the distributions of achievement for the first dimension is (0.30, 0.30, 0.90), that for the second dimension is (0.40, 0.80, 0.90), and that for the third dimension is (0.40, 0.80, 0.90). Therefore, any distributional analysis of human development using the methods presented earlier in this section would result in identical conclusions for both achievement matrices. This is because none of these methods reflect the joint distribution of achievements.

Should, then, any distributional analysis yield the same conclusion? Clearly, in Achievement Matrix I, the third person is the worst off in all dimensions unlike in Achievement Matrix II, where the third person enjoys higher achievement in the second dimension than the second person. Although the dimensional distributions are identical across two distributions, the joint distributions are clearly different. In this sense, one may argue that inequality across the population is higher in Achievement Matrix I than in Achievement Matrix II. In fact, the association between dimensions in Achievement Matrix I is higher, as if the matrix were obtained from Achievement Matrix II by increasing the association between dimensions. In the literature on multidimensional inequality, poverty, and welfare measurement, this type of transformation of achievement matrices is known under different names: basic rearrangement (Boland and Proschan 1988), basic rearrangement-increasing transfer (Tsui 2002), correlation increasing switch (Bourguignon and Chakravarty 2003), correlation increasing arrangement (Deutsch and Silber 2005), association increasing transfer (Seth 2009, 2013), correlation increasing transfer (Tsui 1999), and unfair rearrangement principle (Decancq and Lugo 2012).[2] There is thus a clear need for methods that may capture this second form of inequality.

One such family of indices that incorporates this second as well as the first form of inequality has been proposed by Seth (2009, 2013). These indices, like the family of measures proposed by Foster et al. (2005), are based on generalized means. However, the order of aggregation is different. First, each person's achievements across all dimensions are aggregated using a generalized mean of order β to obtain an overall wellbeing score for each person, and then these overall wellbeing scores are aggregated using a generalized mean of order α to obtain the inequality-adjusted human development index. Thus, the family of indices has two parameters: α and β. When $\alpha = \beta \leq 1$, then the sub-family of indices coincide with the Foster et al. (2005) family of indices. When $\alpha < \beta \leq 1$, then if two joint distributions have identical dimensional distributions but different associations between dimensions, then the level of human development is lower when the association between dimensions is higher.

Seth (2009) applied the index to the same Mexican dataset used by Foster et al. (2005), but because of certain differences in normalizations the final values differ from that of Foster et al. The ranking of 32 states is indeed different when an index sensitive to both forms of inequality is used. However, the point of using such an index can be clarified using an example shown in Table 4, following Seth (2009). The state of Tabasco was chosen at random and the achievements transformed in such a way that each

[2] If Achievement Matrix II is obtained from Achievement Matrix I, the transformation is referred to as 'weak rearrangement' by Alkire and Foster.

dimensional distribution remains unchanged but the association between dimensions increases. **Table 4** summarizes the post-transfer human development scores of Tabasco for different approaches. Note that the development scores of Tabasco that are based on the traditional HDI ($\alpha = \beta = 0$) and the Foster et al. index ($\alpha = \beta = -2$) are the same in the pre- and post-transformation situation. However, Tabasco's level of human development falls when an index sensitive to both forms of inequality is used. Before transformation, Tabasco scored 0.254 whereas after transformation the score drops to 0.244. Therefore, a higher association between dimensions adversely affects Tabasco's level of human development.

Table 4: Level of Human Development Before and After Transformation

State	HDI ($\alpha = 1, \beta = 1$)	Foster et al. (2005) ($\alpha = -2, \beta = -2$)	Seth (2009) ($\alpha = -3, \beta = -1$)
Pre-transformation	0.719	0.296	0.254
Post-transformation	0.719	0.296	0.244

Seth (2013) also applied an index from this family to study the change in wellbeing between 1997 and 2000 in Indonesia using the Indonesian Family Life Surveys. The normalizations of the indicators are slightly different from the normalizations used by Foster et al. (2005) and Seth (2009). Instead of normalizing all variables between zero and one, Seth (2013) pursues an approach analogous to poverty analysis by identifying a threshold for each dimension below which a person is identified as deprived and is otherwise not deprived. Then the achievements of each person in each dimension are divided by the corresponding threshold and these normalized values are assumed to be comparable across dimensions. For example, a person receives a value of one whenever the person is deprived in any dimension. This type of normalization implicitly assumes that the level of wellbeing is not bounded from above. Another major difference in the empirical study of Seth (2013) from Foster et al. (2005) and Seth (2009) is the choice of indicators. Although the same three dimensions – standard of living, education, and health – have been used, standard of living was assessed by per-capita expenditure, education was assessed by years of education completed, and health was assessed by the body mass index. The study focuses only on those who are 15 years or older.

The study produced an interesting finding. When an index with $\alpha = \beta = 1$ (traditional HDI formulation) is used, then no statistically significant change in wellbeing is observed – either at the national level or across rural and urban areas. However, when an index with $\alpha = -1$ and $\beta = 0.1$ is used, then the level of wellbeing increases statistically significantly both at the national level and across rural and urban areas. Why did the level of wellbeing improve when adjusted for inequality? It turns out that although average per-capita expenditure fell between 1997 and 2000, inequality also went down. Even though the pair-wise association between dimensions was higher in 2000 than in 1997, which adversely affects the level of wellbeing, the reduction in inequality within dimensions dominated the increase in association.

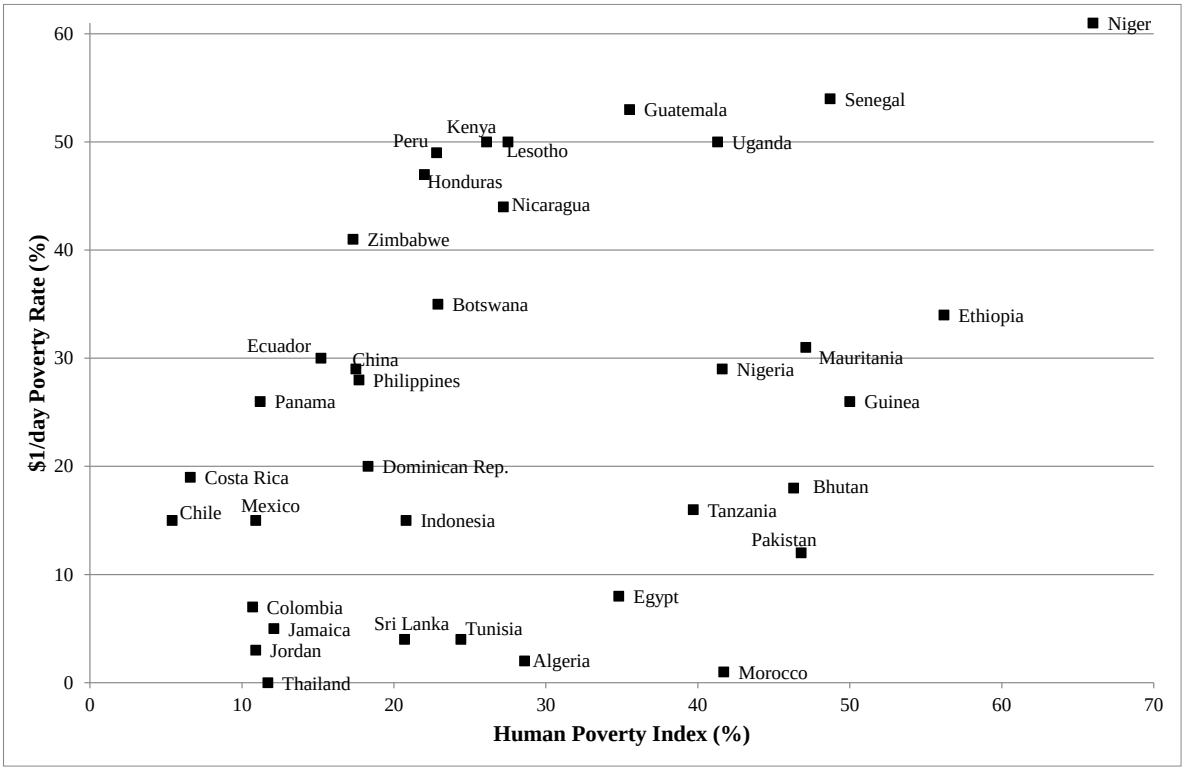
Note that not considering the information regarding joint distribution during multidimensional evaluation is indeed an important omission. On the other hand, an analysis including it requires that

information on all dimensions and indicators should be available for each unit of analysis from the same source. If this requirement appears too stringent, then the distributional analysis may be conducted using the methods outlined earlier in this section. However, given that more and more data have become available in recent years, further research is required to develop methods that reflect both forms of inequality in the multidimensional context.

4. Poverty Analysis and Applications

Both the measurement of human development and its distributional issues are concerned with overall progress without paying particular attention to those who are impoverished. With the objective of dealing with the issue of human impoverishment, Anand and Sen (1997) created the Human Poverty Index (HPI). As they explain, the relationship between the HDI and the HPI should be seen as the relationship between the per-capita Gross National Product, which measures overall progress in terms of incomes, and an income-based index of poverty.

Figure 4: The Relationship between the HPI and $1/day across Developing Countries



Source: Based on Table 1.1 in *Human Development Report 1997*.

In the 1997 edition of the Human Development Report, two separate HPIs were computed for developing countries and for industrialized countries. The HPIs were generalized means of dimensional deprivations (see Seth and Villar 2017 for more detail). The HPIs of developing countries were not found to be highly correlated with the $1/day poverty rates as presented in the 1997 Human Development Report as presented in **Figure 4**. Even though, like the traditional HDI, the HPI was a composite index, it did not earn similar popularity for two main reasons. First, it is not intuitively as

appealing as the HDI. The formulation is not as straightforward as the HDI, and thus it is difficult to provide an intuitive interpretation of the HPI that could be used for meaningful purposes. The second reason is that, unlike the $1/day poverty measure of the World Bank, the HPI could not provide an answer to this question: How many poor are there in a country? For meaningful policy analysis, it is probably more useful to look at deprivation in each indicator separately or at a dashboard of indicators such as those in the Millennium Development Goals.

Table 5: Millennium Development Goals

Goal	Number of Targets	Number of Indicators
1. Eradicate extreme poverty and hunger	2	5
2. Achieve universal primary education	1	3
3. Promote gender equality and empower women	1	4
4. Reduce child mortality	1	3
5. Improve maternal health	1	2
6. Combat HIV/AIDS, malaria, and other diseases	2	7
7. Ensure environmental sustainability	3	8
8. Develop a global partnership for development	7	16
	18	**48**

Source: *Indicators for Monitoring the Millennium Development Goals: Definitions Rationale Concepts and Sources, United Nations* (2003).

In the United Nations Millennium Declaration of 2000, eight Millennium Development Goals, outlined in **Table 5**, consisting of 18 time-bound targets were adopted by 189 countries. In order to accomplish these goals and targets, international organizations such as the World Bank, the International Monetary Fund, the Development Assistance Committee of the Organisation for Economic Co-operation and Development (OECD) joined with the United Nations to agree on 48 indicators. Most of these 18 targets were to be met by 2015.

The goals capture some but not all aspects of human development and human deprivations (UNDP 2003). Goals 1 through 6 are related to three key capabilities for human development. Goal 1 on reducing poverty and hunger is related to the capability of having a decent standard of living. Goals 2 and 3 on achieving universal primary education and promoting gender equality (especially in education) and empowering women are related to the key capability of being educated. And goals 4, 5, and 6 on reducing child mortality, improving maternal health, and combating major diseases is related to the key capability of living a long and healthy life. Goals 7 (ensuring environmental sustainability) and 8 (develop a global partnership for development) are not directly related to a key capability, but are related to essential conditions for human development.

Progress since 2000, however, has not been uniform across all indicators. As the data in **Table 6** reflect, 70 or more developing countries either met the targets or made sufficient progress in indicators such as extreme poverty, improved water, education gender parity; however, another 70 or more countries either made insufficient progress or were moderately to seriously off-target with respect to indicators such as under-5 mortality, under-nourishment, improved sanitation, maternal mortality, and infant mortality. In

fact, only 26 developing countries met the target or made sufficient progress in improving maternal mortality, and only 14 countries met the target or made sufficient progress in improving infant mortality.

Table 6: Number of Developing Countries with Progress Status in Selected MDG Indicators

Goal	Target/Indicator	MDG Target Met	Sufficient Progress	Insufficient Progress	Moderately Off Target	Seriously Off Target
1	Extreme Poverty ($1.25/day)	66	12	7	4	24
7	Improved Water	64	6	4	11	40
3	Education Gender Parity	61	12	8	8	32
2	Primary Completion	44	9	10	9	44
4	Under-5 Mortality	35	14	20	34	39
1	Under-nourishment	34	7	9	7	70
7	Improved Sanitation	32	10	8	8	60
5	Maternal Mortality	8	18	7	26	74
4	Infant Mortality	6	9	18	32	77

Source: Downloaded from the World Bank website at http://data.worldbank.org/mdgs/progress-status-across-groups-number-of-countries on 30 April 2014.

Indeed, a dashboard of indicators conveys more information in terms of progress in different dimensions. It conveys better than a composite index where progress has been made and where progress has not. However, a dashboard of indicators has certain limitations. First, it lacks of a single outline figure like GDP. If one looks at the MDGs to learn whether a country has made progress or not, a conclusion can only be reached if the country has improved in all indicators or the country has deteriorated in all indicators. Apart from these two cases, it is hard to make any conclusion on progress. It is very difficult to go through all 48 indicators every time to draw any conclusion. Second, although a dashboard of indicators shows how many people are deprived in various indicators, it does not reflect how many people are poor at a certain point in time (Alkire, Foster, and Santos 2011). Third, a dashboard of indicators, like any composite index (such as the HPI), does not consider the joint distribution of deprivations. For further discussions of these issues, see Chapter 3 of Alkire et al. (2015).

Let us consider the following example, drawing on Alkire and Foster (2011). It is similar in spirit to the example presented in the previous section.

Deprivation Matrix I

$$\begin{array}{ccc} \text{Income} & \text{Health} & \text{Sanitation} \\ \end{array}$$
$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Deprivation Matrix II

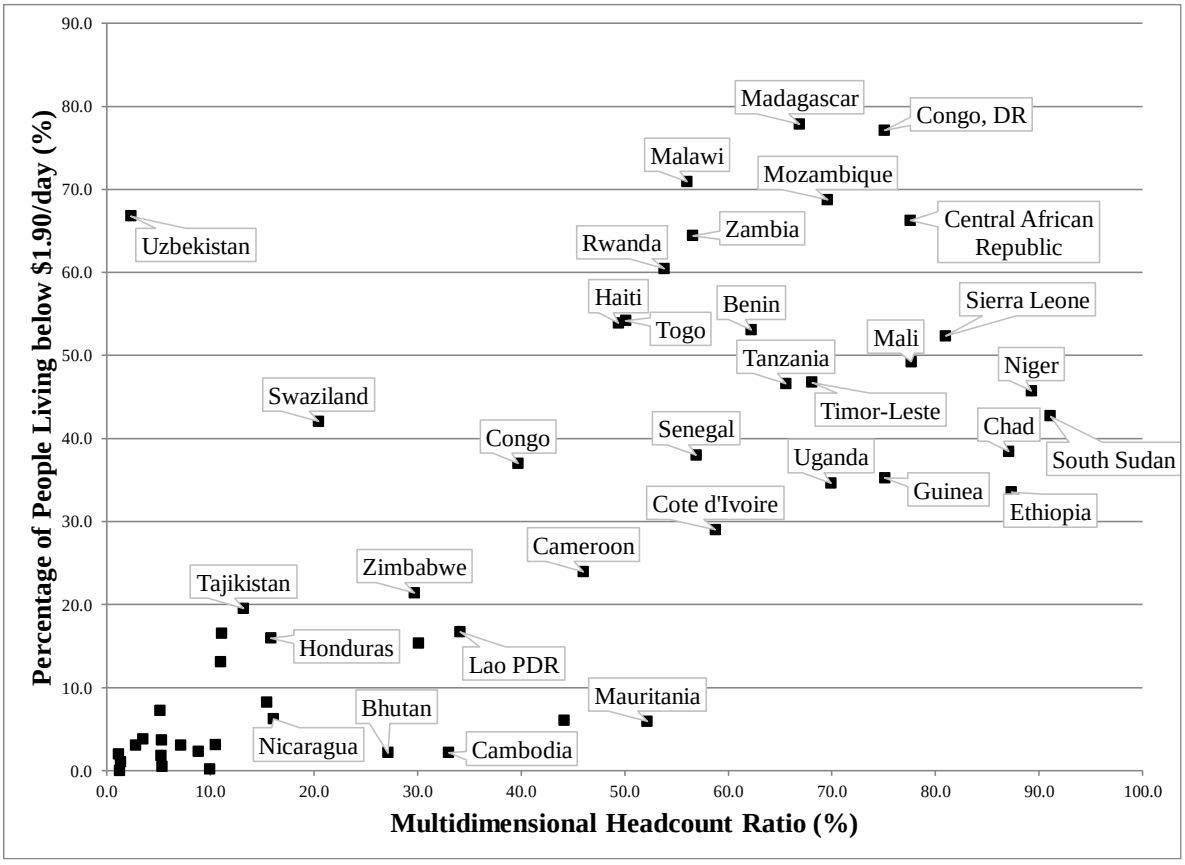
$$\begin{array}{ccc} \text{Income} & \text{Health} & \text{Sanitation} \\ \end{array}$$
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

Suppose there are two hypothetical societies with three persons. The deprivation profile of the two societies in three MDG indicators are summarized in Deprivation Matrices I and II, where rows denote persons. In the matrix, an element equal to one implies that the person is deprived in the indicator; whereas, if the element is equal to zero, it implies that the person is not deprived. It is clear that in Deprivation Matrix I, each person has one deprivation. On the other hand, in Deprivation Matrix II, only one person faces all three deprivations. Both a composite index (such as the HPI) and a dashboard of indicators (for example, consisting of the three indicators) would find an identical level of poverty in

these two societies. In other words, neither composite indices nor dashboards of indicators can identify such differences. Why is understanding such differences crucial in practice? Note that, in order to alleviate these deprivations in the second society, it is more efficient if the three different ministries responsible for these three indicators coordinate with each other to assist the person facing all deprivations. The second reason is that it may be possible in the second society, unlike in the first society, that the third person actually represents a minority group living in abject poverty within an affluent society.

Any poverty measurement exercise, following Sen (1976), involves two important steps: identification and aggregation. The identification step amounts to singling out who the poor are. This crucial step was ignored by both the HPI and the dashboard of MDG indicators. In the innovative 2010 Human Development Report, the new Multidimensional Poverty Index (developed by Alkire and Santos 2010) respected these two steps. The construction of the MPI and its properties are outlined in detail in Seth and Villar (2017). The MPI identifies a person as poor if the person is deprived in a third or more of the ten weighted indicators. The MPI does not necessarily identify the same group of people identified as living below $1.90/day – the income poverty threshold used by the World Bank to assess global income poverty (Ferreira et al., 2016).

Figure 5: Disparity between $1.90/Day Poverty Rates and MPI Poverty Rates across Developing Countries

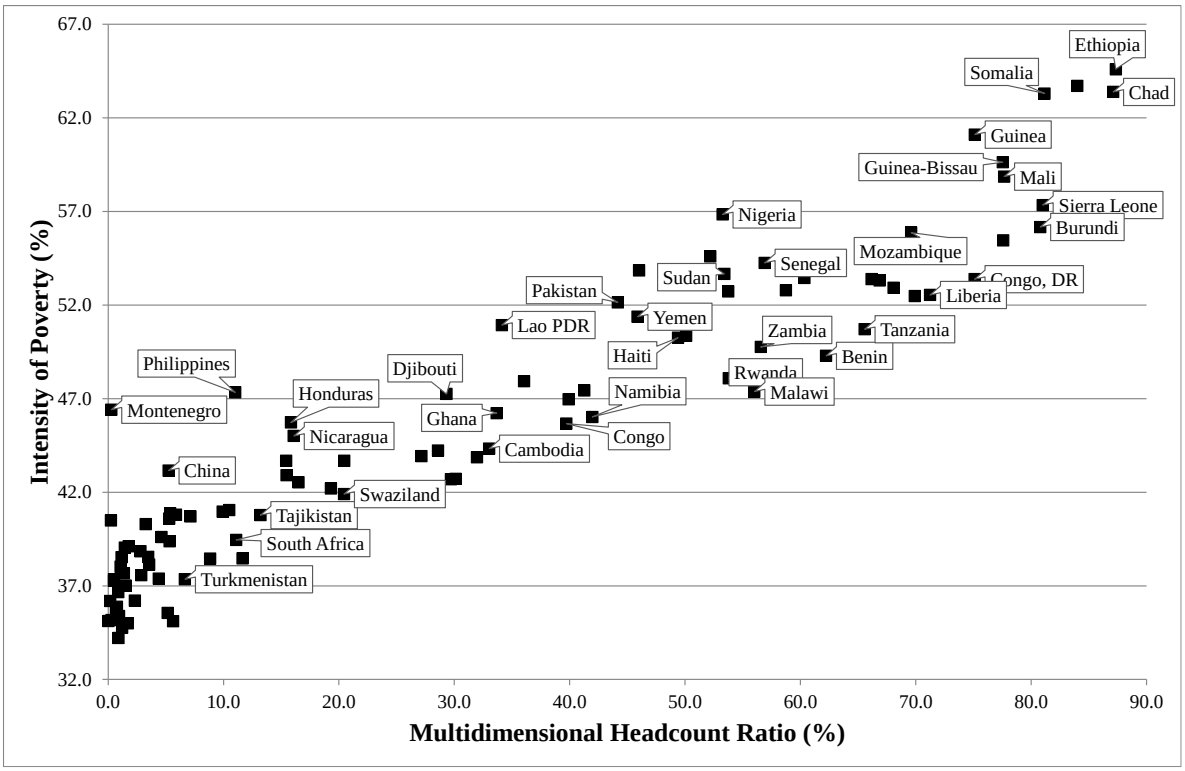


Source: The data used from Alkire et al. (2016) accessed on 31 January 2017 obtained at http://www.ophi.org.uk/multidimensional-poverty-index/mpi-2015/mpi-data/.

In **Figure 5**, we compare the percentage of population identified as living below $1.90/day and the percentage of the population identified as the MPI poor. Although there appears to be a positive correlation, there are several exceptions. For example, let us look at countries where 40–50% of the population live below $1.90/day: Swaziland, Tanzania, Timor-Leste, Mali, South Sudan, and Niger. Multidimensional headcount ratios for these countries, however, vary from 20% to 91%. Several other similar examples may be found in Figure 5. Inter-temporal analyses have also shown that reductions in monetary poverty and MPI poverty do not go hand in hand. For a cross-country example, see Alkire, Roche, and Vaz (2015) and for an application in India, see Alkire and Seth (2015).

The MPI has three interesting features that make it amenable to empirical applications. These features are (i) the MPI is presented as a product of the percentage of the population that is poor (known as the Multidimensional Headcount Ratio or the incidence of poverty) and the average number of weighted deprivations that the poor people experience (known as the intensity of poverty), (ii) the MPI is additively decomposable so that the national MPI can be expressed as a population-weighted average of subgroup MPIs, and (iii) the MPI can be expressed as a weighted average of post-identification dimensional deprivations.

Figure 6: Incidence Vs. Intensity of Poverty



Source: Data from Alkire et al. (2016), accessed on 31 January 2016 at http://www.ophi.org.uk/multidimensional-poverty-index/mpi-2015/mpi-data/.

The usefulness of the first property can be seen in the example in **Figure 6**, where we plot the relationship between the incidence and intensity of poverty across developing countries. The MPI is a product of incidence and intensity, and thus it may be possible that the same level of MPI can be obtained by different combinations of incidence and intensity. If the same level of MPI is obtained from

a lower level of incidence but a higher level of intensity, then this means that a smaller fraction of poor people are deprived in a larger number of indicators on average. Let us compare Sierra Leone and Nigeria.

Nearly 81% of the population is MPI poor in Liberia compared to only around 53% of the population in Nigeria. However, the poor experience, on average, similar levels of poverty intensity in both countries. Several other examples can be found in Figure 6. The incidence and intensity breakdown is also useful for inter-temporal analysis. While analyzing the evolution of multidimensional poverty in India using MPI, Alkire and Seth (2015) found that in some states, the reduction in MPI was the result of stronger reductions in incidence; while in other states the strong reduction in poverty was due to relatively larger reductions in intensity.

The other two properties have also been used in various country studies. Roche (2013), for example, studied multidimensional child poverty in Bangladesh between 1997 and 2007 and used the dimensional breakdown property to understand the dynamics of poverty reduction. Roche found that the reduction in poverty in Barisal province was due to a large reduction in water deprivation, whereas in other provinces, such as Chittagong and Khulna, the reduction was mostly driven by health and nutrition. Alkire and Seth (2015) used the subgroup decomposition property while studying the reduction in multidimensional poverty in India between 1999 and 2006. They found that, although there was a modest reduction in national multidimensional poverty, the poorest population subgroups (i.e., states, castes, and religions) made the slowest progress. For further applications of the MPI in the measurement and analysis of poverty, see Batana (2013), Saini (2013), and Alkire and Seth (2013). For a more detailed discussion of the MPI methodology and applications, see Alkire et al. (2015).

5. Concluding Remarks

This paper provides a brief outline of the practical issues surrounding the measurement of human development and poverty. The key aspects are multidimensionality, inequality, and poverty – three elements for which there is a large list of contributing factors and a variety of modelling choices.

Discussing multidimensionality implies analysing how to select the relevant dimensions of a given problem, deciding how to weigh their relative importance, and choosing how to aggregate (or not) those dimensions into a single indicator. A dashboard of indicators is sometimes regarded as a better practical choice because it saves the analyst from making those difficult modelling choices. Yet single-valued indicators provide a summary measure of a complex phenomenon, making it easier to grasp the evolution of human development and poverty. Be that as it may, there are two considerations worth introducing here. First, that both approaches can be regarded as complementary rather than as alternative. So a single-valued indicator coupled with additional information on particular aspects of human development may be very useful. Second, in both scenarios, one has to deal with the problem of interdependent variables in order to get a sound assessment of the situation.

In the case of multidimensional measures, we find the choice of three equally weighted dimensions to be the most common. This choice seems an acceptable approach regarding the equal weights of those three dimensions even though, sooner rather than later, the sustainability dimension should be introduced. Substituting the arithmetic mean with the geometric mean, as a way of aggregating those dimensions, seems a substantial improvement, even though there are still some pending issues, particularly regarding the normalization strategy and the use of logs for the income dimension (see Seth and Villar 2017). As a consequence, the resulting rates of substitution for those countries with lower levels of human development may become rather odd.

Taking distributive aspects into account is a major step forward in the measurement of human development. In spite of the different proposals made at different points in time, it took 20 years to introduce this aspect into the assessment of human development. The method for incorporating inequality into the measurement of human development has so far been intuitive and solid. Yet there are still some inconsistencies: income is measured in logs whereas income distribution is measured without. There are also some difficulties in interpreting what inequality means with respect to education and health, as it is not clear that a uniform distribution dominates another in which the younger generation exhibits higher values.

The measurement of poverty has been substantially revised since 2010. It now consists of a multidimensional index that applies to less-developed countries and is much richer and sounder than former proposals. Yet it is somehow unfortunate to lose the poverty index for highly developed countries at a time when the economic crisis hit some sectors of those countries very hard.

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Appendix

Human Development Index (HDI), Inequality Adjusted Human Development Index (IAHDI) and Multidimensional Poverty Index 2013

HDI Rank	Country	HDI	IAHDI	Loss Due to Inequality (%)	Rank Difference of HDI and IHDI	MPI
Very High Human Development						
1	Norway	0.944	0.891	5.6	0	..
2	Australia	0.933	0.860	7.8	0	..
3	Switzerland	0.917	0.847	7.7	-1	..
4	Netherlands	0.915	0.854	6.7	1	..
5	United States	0.914	0.755	17.4	-23	..
6	Germany	0.911	0.846	7.1	1	..
7	New Zealand	0.910	..	..	..	..
8	Canada	0.902	0.833	7.6	-2	..
9	Singapore	0.901	..	..	..	..
10	Denmark	0.900	0.838	6.9	0	..
11	Ireland	0.899	0.832	7.5	-1	..
12	Sweden	0.898	0.840	6.5	3	..
13	Iceland	0.895	0.843	5.7	5	..
14	United Kingdom	0.892	0.812	8.9	-4	..
15	Hong Kong, China (SAR)	0.891	..	..	..	..
15	Korea (Republic of)	0.891	0.736	17.4	-20	..
17	Japan	0.890	0.779	12.4	-6	..
18	Liechtenstein	0.889	..	..	..	..
19	Israel	0.888	0.793	10.7	-4	..
20	France	0.884	0.804	9.0	-2	..
21	Austria	0.881	0.818	7.2	4	..
21	Belgium	0.881	0.806	8.5	0	..
21	Luxembourg	0.881	0.814	7.6	3	..
24	Finland	0.879	0.830	5.5	9	..
25	Slovenia	0.874	0.824	5.8	9	0.000
26	Italy	0.872	0.768	11.9	-1	..
27	Spain	0.869	0.775	10.9	1	..
28	Czech Republic	0.861	0.813	5.6	9	0.010
29	Greece	0.853	0.762	10.6	0	..
30	Brunei Darussalam	0.852	..	..	..	..
31	Qatar	0.851	..	..	..	..
32	Cyprus	0.845	0.752	11.0	-3	..

33	Estonia	0.840	0.767	8.7	3	0.026
34	Saudi Arabia	0.836	..	..	..	..
35	Lithuania	0.834	0.746	10.6	-3	..
35	Poland	0.834	0.751	9.9	-2	..
37	Andorra	0.830	..	..	..	..
37	Slovakia	0.830	0.778	6.3	9	0.000
39	Malta	0.829	0.760	8.3	5	..
40	United Arab Emirates	0.827	..	..	..	0.002
41	Chile	0.822	0.661	19.6	-16	..
41	Portugal	0.822	0.739	10.1	0	..
43	Hungary	0.818	0.757	7.4	7	0.016
44	Bahrain	0.815	..	..	..	..
44	Cuba	0.815	..	..	..	..
46	Kuwait	0.814	..	..	..	..
47	Croatia	0.812	0.721	11.2	-2	0.016
48	Latvia	0.810	0.725	10.6	0	0.006
49	Argentina	0.808	0.680	15.8	-4	0.011
High Human Development						
50	Uruguay	0.79	0.662	16.1	-8	0.006
51	Bahamas	0.789	0.676	14.3	-3	..
51	Montenegro	0.789	0.733	7.2	5	0.006
53	Belarus	0.786	0.726	7.6	6	0.000
54	Romania	0.785	0.702	10.5	4	..
55	Libya	0.784	..	..	..	..
56	Oman	0.783	..	..	..	..
57	Russian Federation	0.778	0.685	12	3	0.005
58	Bulgaria	0.777	0.692	11	5	..
59	Barbados	0.776	..	..	..	..
60	Palau	0.775	..	..	..	..
61	Antigua and Barbuda	0.774	..	..	..	..
62	Malaysia	0.773	..	..	..	..
63	Mauritius	0.771	0.662	14.2	-2	..
64	Trinidad and Tobago	0.766	0.649	15.2	-6	0.020
65	Lebanon	0.765	0.606	20.8	-17	..
65	Panama	0.765	0.596	22.1	-18	..
67	Venezuela (Bolivarian Republic of)	0.764	0.613	19.7	-10	..
68	Costa Rica	0.763	0.611	19.9	-11	..
69	Turkey	0.759	0.639	15.8	-3	0.028
70	Kazakhstan	0.757	0.667	11.9	9	0.001
71	Mexico	0.756	0.583	22.9	-13	0.011

71	Seychelles	0.756	..	..	..	..
73	Saint Kitts and Nevis	0.75	..	..	..	..
73	Sri Lanka	0.75	0.643	14.3	1	0.021
75	Iran (Islamic Republic of)	0.749	0.498	33.6	-34	..
76	Azerbaijan	0.747	0.659	11.8	7	0.021
77	Jordan	0.745	0.607	18.6	-5	0.008
77	Serbia	0.745	0.663	10.9	12	0.000
79	Brazil	0.744	0.542	27	-16	0.011
79	Georgia	0.744	0.636	14.5	4	0.003
79	Grenada	0.744	..	..	..	..
82	Peru	0.737	0.562	23.7	-9	0.043
83	Ukraine	0.734	0.667	9.2	18	0.008
84	Belize	0.732	..	..	..	0.018
84	Macedonia (Former Yugoslav Republic of)	0.732	0.633	13.6	7	0.002
86	Bosnia and Herzegovina	0.731	0.653	10.6	13	0.002
87	Armenia	0.73	0.655	10.4	15	0.001
88	Fiji	0.724	0.613	15.3	6	..
89	Thailand	0.722	0.573	20.7	-2	0.006
90	Tunisia	0.721	..	..	..	0.004
91	China	0.719	..	..	..	0.056
91	Saint Vincent and the Grenadines	0.719	..	..	..	..
93	Algeria	0.717	..	..	..	..
93	Dominica	0.717	..	..	..	0.018
95	Albania	0.716	0.62	13.4	11	0.005
96	Jamaica	0.715	0.579	19	1	..
97	Saint Lucia	0.714	..	..	..	..
98	Colombia	0.711	0.521	26.7	-10	0.022
98	Ecuador	0.711	0.549	22.7	-3	0.024
100	Suriname	0.705	0.534	24.2	-6	0.024
100	Tonga	0.705	..	..	..	..
102	Dominican Republic	0.7	0.535	23.6	-4	0.009
Medium Human Development						
103	Maldives	0.698	0.521	25.4	-7	0.018
103	Mongolia	0.698	0.618	11.5	16	0.065
103	Turkmenistan	0.698	..	..	..	..
106	Samoa	0.694	..	..	..	..
107	Palestine, State of	0.686	0.606	11.7	13	0.005
108	Indonesia	0.684	0.553	19.2	5	0.066
109	Botswana	0.683	0.422	38.2	-21	..
110	Egypt	0.682	0.518	24	-5	..

111	Paraguay	0.676	0.513	24.1	-5	0.064
112	Gabon	0.674	0.512	24	-5	0.070
113	Bolivia (Plurinational State of)	0.667	0.47	29.6	-10	0.089
114	Moldova (Republic of)	0.663	0.582	12.2	16	0.007
115	El Salvador	0.662	0.485	26.7	-7	..
116	Uzbekistan	0.661	0.556	15.8	14	0.008
117	Philippines	0.66	0.54	18.1	10	0.064
118	South Africa	0.658	..	..	..	0.044
118	Syrian Arab Republic	0.658	0.518	21.2	4	0.021
120	Iraq	0.642	0.505	21.4	0	0.045
121	Guyana	0.638	0.522	18.2	10	0.030
121	Viet Nam	0.638	0.543	14.9	15	0.017
123	Cape Verde	0.636	0.511	19.7	4	..
124	Micronesia (Federated States of)	0.63	..	..	..	..
125	Guatemala	0.628	0.422	32.8	-8	0.127
125	Kyrgyzstan	0.628	0.519	17.2	10	0.019
127	Namibia	0.624	0.352	43.6	-22	0.187
128	Timor-Leste	0.62	0.43	30.7	-3	0.360
129	Honduras	0.617	0.418	32.2	-6	0.072
129	Morocco	0.617	0.433	29.7	0	0.048
131	Vanuatu	0.616	..	..	..	0.129
132	Nicaragua	0.614	0.452	26.4	4	0.072
133	Kiribati	0.607	0.416	31.5	-4	..
133	Tajikistan	0.607	0.491	19.2	9	0.054
135	India	0.586	0.418	28.6	0	0.283
136	Bhutan	0.584	0.465	20.4	9	0.119
136	Cambodia	0.584	0.44	24.7	7	0.212
138	Ghana	0.573	0.394	31.3	-1	0.139
139	Lao People's Democratic Republic	0.569	0.43	24.5	8	0.174
140	Congo	0.564	0.391	30.7	0	0.181
141	Zambia	0.561	0.365	35	-4	0.328
142	Bangladesh	0.558	0.396	29.1	4	0.253
142	Sao Tome and Principe	0.558	0.384	31.2	0	0.154
144	Equatorial Guinea	0.556	..	..	..	..
Low Human Development						
145	Nepal	0.54	0.384	28.8	3	0.217
146	Pakistan	0.537	0.375	30.1	2	0.230
147	Kenya	0.535	0.36	32.8	0	0.229
148	Swaziland	0.53	0.354	33.3	-2	0.086
149	Angola	0.526	0.295	44	-17	..

150	Myanmar	0.524	..	..	..	..
151	Rwanda	0.506	0.338	33.2	-4	0.350
152	Cameroon	0.504	0.339	32.8	-2	0.248
152	Nigeria	0.504	0.3	40.3	-14	0.240
154	Yemen	0.5	0.336	32.8	-2	0.283
155	Madagascar	0.498	0.346	30.5	2	0.357
156	Zimbabwe	0.492	0.358	27.2	7	0.172
157	Papua New Guinea	0.491	..	..	..	..
157	Solomon Islands	0.491	0.374	23.8	11	..
159	Comoros	0.488	..	..	..	..
159	Tanzania (United Republic of)	0.488	0.356	27.1	8	0.332
161	Mauritania	0.487	0.315	35.3	-2	0.352
162	Lesotho	0.486	0.313	35.6	-2	0.156
163	Senegal	0.485	0.326	32.9	3	0.439
164	Uganda	0.484	0.335	30.8	5	0.367
165	Benin	0.476	0.311	34.6	0	0.412
166	Sudan	0.473	..	..	..	..
166	Togo	0.473	0.317	32.9	4	0.250
168	Haiti	0.471	0.285	39.5	-3	0.248
169	Afghanistan	0.468	0.321	31.4	7	0.353
170	Djibouti	0.467	0.306	34.6	2	0.139
171	Côte d'Ivoire	0.452	0.279	38.3	-2	0.310
172	Gambia	0.441	..	..	..	0.324
173	Ethiopia	0.435	0.307	29.4	5	0.564
174	Malawi	0.414	0.282	31.9	1	0.334
175	Liberia	0.412	0.273	33.8	-1	0.485
176	Mali	0.407	..	..	..	0.558
177	Guinea-Bissau	0.396	0.239	39.6	-4	0.462
178	Mozambique	0.393	0.277	29.5	2	0.389
179	Guinea	0.392	0.243	38	-1	0.506
180	Burundi	0.389	0.257	33.9	2	0.454
181	Burkina Faso	0.388	0.252	35	2	0.535
182	Eritrea	0.381	..	..	..	..
183	Sierra Leone	0.374	0.208	44.3	-3	0.388
184	Chad	0.372	0.232	37.8	1	0.344
185	Central African Republic	0.341	0.203	40.4	-2	0.430
186	Congo (Democratic Republic of the)	0.338	0.211	37.6	1	0.392
187	Niger	0.337	0.228	32.4	3	0.605

Source: *Human Development Report* 2014