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<th>Multidimensional Poverty Rankings based on Pareto Principle: A Practical Extension</th>
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Multidimensional Poverty Rankings based on Pareto Principle: A Practical Extension

Maki Michinaka
Takahiro Ito

May 2010
Multidimensional Poverty Rankings based on Pareto Principle: A Practical Extension

Michinaka, Maki * and Takahiro Ito †

March 30, 2010

Abstract

This paper proposes a ranking method of multidimensional poverty and extends it aiming to enhance its practical utility. While our original ranking method that assumes non-comparability among different dimensions of poverty succeeds in eliminating some implicit arbitrariness in existing ranking, it also confronts a disadvantage that a non-negligible number of objectives (countries) are ranked at the same level. In order to improve this disadvantage, we propose an extended ranking method, where we allow the data to have a certain range of bandwidth. The introduction of bandwidth improves the usefulness of our ranking in the sense that it decreases the number of countries with the same rank. In addition, a simulation exercise shows that this extension also improves the robustness of the ranking against measurement errors.

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1 Introduction

This paper focuses on issues of multidimensional poverty measurement and ranking. A multidimensional poverty approach regards poverty not only as an economical connotation but also as a multifaceted one including various non-economical factors such as health, education, social exclusion and safety.

Literature on multidimensional poverty measurement can be traced back to early contributions like the physical quality of life index by Morris (1979), the deprivation index by Townsend (Townsend et al. 1989), and the quality of life index by Dasgupta and Weale (1992). However, only in recent years have a number of studies tried to establish theory-based conceptions and methods to measure multidimensional poverty, based on the pioneering works.

Existing studies in this field can be broadly classified into two strands: statistical and non-statistical approaches. In the former, some sort of latent variable models are often employed. A latent variable model regards multidimensional poverty as an unobserved endogenous variable determined by several exogenous variables such as social, political and institutional factors. This kind of statistical analysis enables us to investigate the causal relationship among different dimensions of poverty.¹

On the other hand, non-statistical approaches can be divided into a further two sub-categories: the fuzzy set approach and the multidimensional poverty ordering approach. The former explicitly takes into account the vagueness of multidimensional poverty. The

¹For more details on this topic, see Krishnakumar and Ballon (2008), Asselin (2009) and Kuklys (2005).
terms ‘the poor’ and ‘the non-poor’ may bring some ambiguity, even in the context of unidimensional (e.g. income-based) poverty. Despite this, a number of studies dichotomize the poor and non-poor by a sole poverty line. The fuzzy set approach aims to capture this ambiguity by employing so-called ‘membership functions’ that describe the degree of poverty, and succeeds in dealing with the dynamics of poverty (Qizilbash, 2006; Betti et al., 2008). The multidimensional poverty ordering approach is inspired by a pioneering work on the characterization of poverty index by Sen (1976). This approach consists of two stages. In the first, who is poor and to what extent are determined. For a set of individuals, the subset to which the poor belong is defined and the level of poverty for the set is expressed as an index value. Such poverty indices are usually characterized by an axiomatic basis, with aggregation of the shortfalls of the poor falling below a certain poverty line. The next stage provides some kinds of ranking rules to order sets of individuals in accordance with the level of multidimensional poverty. The majority adopt stochastic dominance criteria or its applications (Chakravarty and Bourguignon 2002; Tsui, 2002; Velez and Robles, 2008).

With these studies taken as the starting point, this paper proposes an alternative ranking methodology for multidimensional poverty. Whereas our method can be classified as a multidimensional poverty ordering approach, the approach in this paper can be distinguished from others. Our approach is based on the significant assumption that we allow the non-comparability of one dimension of multidimensional poverty with another. This reflects the implicit belief that we can never compare the value of poverties over
dimensions because a distinct dimension represents a distinct aspect of poverty. However, this belief also highlights a practical disadvantage of the ranking, whereby many objectives are ranked at the same level. In typical rankings, one objective corresponds to one rank, but multiple objectives may have equivalent rank in our approach. Consequently, the ranking yielded by our approach is possibly coarser than other typical rankings in the sense that many non-comparable objectives remain. Due to this disadvantage, dominance order ranking is subject to the criticism that it lacks practical utility, despite successfully eliminating implicit arbitrariness in existing measures.

In order to alleviate the coarseness of the ranking, we propose an extended ranking method, where we allow the data to have a certain range of bandwidth. The introduction of bandwidth is also interpretable as neglecting a certain range of differences between the data, and doing this turns many countries from non-comparable to comparable. Thus, the extended ranking method can improve the usefulness of the ranking in the sense that it decreases the number of countries with the same rank. In addition, this extension has a secondary effect: the extended method of ranking is more robust to measurement errors than the original method, since allowing the data to have a bandwidth is equivalent to presuming that the data have measurement errors. We will confirm this by conducting a simulation exercise.

The rest of this paper is organized as follows. The next section reviews the framework of the dominance order ranking and its extension. Section 3 examines the ranking results derived from the original and extended method, and shows the result of a simulation.
exercise. We conclude in the final section.

2 Dominance Order Ranking and Its Practical Extension

2.1 Reviewing the dominance order ranking

Before proceeding to explain the extended method of the dominance order ranking proposed by Michinaka (2009), we review the concept of Michinaka’s ranking method and its advantages and drawbacks. Let us assume that the level of multidimensional poverty for each country is expressed by the multidimensional development profile, which is a bundle of the values of multiple indicators representing the level of poverty, such as GDP per capita, infant mortality rate, and adult literacy rate. These indicators are common among all objectives (e.g. individuals, countries or societies) to be ranked. We also assume that the value of each indicator is a real positive number. Note that the basis for the information in our approach is the degree of development, although most existing approaches use the degree of deprivation for the same basis, based on some sort of poverty lines. This is why we refer to a ‘multidimensional development profile’ instead of ‘multidimensional poverty profile.’ As stated in the previous section, we eliminate the implicit arbitrariness included in all poverty lines.

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2Michinaka (2009) proposes three different ranking methods based on the concept of the Pareto dominance: minimal order ranking (MINOR), maximal order ranking (MAXOR) and Pareto dominance order ranking (PDOR). In what follows, unless otherwise noted, we use the term ‘dominance order ranking’ to refer to ‘MAXOR.’
The dominance order ranking is formulated as follows. Let \( C \) be the set of countries and \( I \) be the set of the poverty indicators. The number of elements in \( C \) and \( I \) is denoted by \( \#C \) and \( \#I \), respectively. The level of multidimensional development for any countries in \( C \) is expressed as \( f(c) = (f^i_c)_{i \in I} \) where \( f(\cdot) \) is a mapping that assigns the \( \#I \)-dimensional poverty level to a country \( c \) in \( C \).

Regarding binary relations determining a ranking, we let \( \succeq \) denote the binary relation on \( C \) that means ‘at least as developed as,’ defined as \( c \succeq \hat{c} :\iff \forall c, \hat{c} \in C \& \forall i \in I, f^i_c \geq f^i_{\hat{c}}. \) Corresponding to this binary relation, we now define the three binary relations on \( C \); (1) \( \succ \) means ‘strictly more developed than’ and is defined as \( \forall c, \hat{c} \in C, \& \forall i \in I, c \succ \hat{c} :\iff f^i_c > f^i_{\hat{c}} \) such that \( f^i_c \geq f^i_{\hat{c}}, \) (2) \( \sim \) means ‘as developed as’ and is defined as \( c \sim \hat{c} :\iff \forall c, \hat{c} \in C, \& \forall i \in I, f^i_c = f^i_{\hat{c}}, \) and (3) \( \bowtie \) means ‘non-comparable’ and is defined as \( c \bowtie \hat{c} :\iff \forall c, \hat{c} \in C, \exists i \in I \) such that \( f^i_c > f^i_{\hat{c}} \) & \( \exists j \in I \) such that \( f^j_c < f^j_{\hat{c}}. \) \( \succ \) and \( \sim \) are the asymmetric and symmetric factors of \( \succeq, \) and \( \bowtie \) is an incomparability relationship corresponding to \( \succeq \): namely \( c \bowtie \hat{c} \iff \neg(c \succeq \hat{c}) \& \neg(\hat{c} \succeq c). \) \(^3\) Since the binary relation \( \succ \) describes Pareto dominance, if \( c \succ \hat{c} (\forall c, \hat{c} \in C), \) then \( c \) is interpreted as dominating \( \hat{c}. \)

Using the above binary relations, we now define the dominance order ranking. First of all, we define a maximal set of \( X \) as follows:

\[
\mathcal{M}(X, \succ) = \{ x \mid x \in X \& \text{there is no } y \in X \text{ such that } y \succ x \}
\]

Utilizing the concept of maximal sets, the dominance order ranking is generated by repeating the following steps:

\(^3\)The symbol \( \neg \) denotes the negation of a logical statement.
(step 1) Make the maximal set on $C$, and call it $\mathcal{M}_1$, and define the (relative) complement of $\mathcal{M}_1$ in $C$ ($C \setminus \mathcal{M}_1$) as $C_1$.

(step 2) Again, make the maximal set $\mathcal{M}_2$ on $C_1$, namely,

$$\mathcal{M}_2(C_1, \succ) = \{ c \mid c \in C_1 \text{ and there is no } \hat{c} \in C_1 \text{ such that } \hat{c} \succ c \}.$$ and define $C_1 \setminus \mathcal{M}_2)$ as $C_2$.

(step 3) In the same manner, make the maximal set $\mathcal{M}_r$ on $C_{r-1}$ until $C_{r-1} \setminus \mathcal{M}_r = \emptyset$.

Consequently, this procedure yields a sequence of maximal sets, namely, $\mathcal{M}_1, \mathcal{M}_2, \ldots, \mathcal{M}_r, \ldots, \mathcal{M}_R$. The subscript $r$ of $\mathcal{M}_r$ corresponds to the rank of the countries belonging to the maximal set.

Thus, the processes of making a dominance order ranking are equivalent to that of making a partition of a set. These processes require no aggregation or indexation of different development indices. In this sense, the dominance order ranking succeeds in eliminating the implicit arbitrariness associated with the aggregation, and this is attributed to the fact that the ranking is based solely on the ordinal relationship between the values of indices.

However, owing to this fundamental non-comparability between different indices, the dominance order ranking has the drawback of ‘tie-full tendency.’ It means many countries are ranked at the same rank, and things will worsen as the dimension of development or poverty indices ($\sharp I$) increases.$^4$

Due to this disadvantage, the dominance order ranking is subject to the criticism that it lacks practical utility even though it is convincing, less arbitrary and intuitively

$^4$Regarding other advantages and disadvantages, see Michinaka (2009).
understandable. In the next subsection, we propose a method to improve the drawback of the tie-full tendency.

2.2 Allowing a Bandwidth of Data

For simplicity’s sake, consider a case where there are only two indices ($\#I = 2$) denoted by $x$ and $y$. Figure 1 depicts the way of the dominance order ranking. Focusing on country D in the first panel, the tie-full tendency is related to the shaded square areas lying to the northwest and southeast of D. We refer to these areas as ‘non-comparable areas’ of D, since countries B, C, E and G in these areas are non-comparable to D. The tie-full tendency is mainly attributed to these non-comparable areas, and consequently, reducing the area is largely equivalent to improving the tie-full tendency.

In fact, there are several ways to reduce the area. For instance, approaches admitting a cardinality among values of multiple indicators, like the Human Development Index (HDI), mean arbitrary weights are placed on each indicator. Consequently, any pairs of $f(c) = (f_i^c)_{i \in I}$ and $f(\hat{c}) = (f_i^{\hat{c}})_{i \in I}$ for all $c, \hat{c} \in C$ are comparable since $f(c) = (f_i^c)_{i \in I}$ for all $c \in C$ can be a scalar as an aggregated index value (in short, there is no non-comparable area).

One of the ways to decrease in a dimension of the non-comparable areas, while maintaining the advantage of the dominance order ranking, is to allow the data of the indicators to have a certain range of bandwidth (the second panel of Figure 1). This is also interpretable as neglecting a certain range of differences between the values of indicators, or
equivalent to presuming that the data have measurement errors. Considering the fact that country-level data potentially contain a certain level of measurement errors, allowing data to have a bandwidth (as $d^x$ and $d^y$ in the second panel) can be justified to some extent and is also plausible from a practical perspective. As the figure shows, doing this makes the area decreased, and means countries C and E can escape from the non-comparable areas of D.

At the same time, however, this approach also has a weakness: the existence of the bandwidth generates an area within which all values are regarded as indifferent. In the second panel of Figure 1, this is depicted as the area bounded by the solid line and referred to as ‘indifference area’ of D. Due to this area, the country F is reclassified from the category of comparable to indifferent.

Thus, the introduction of a bandwidth has an advantage and disadvantage: whereas the number of countries reclassified from the category of non-comparable (i.e. $c \triangleright \hat{c}$) to comparable (i.e. $c > \hat{c}$ or $\hat{c} > c$), denoted by $\sharp M$, increases, the same applies to that moving from comparable to indifferent (i.e. $c \sim \hat{c}$), as denoted by $\sharp D$. Regarding $\sharp M$ and $\sharp D$ as the benefit and cost of introducing a bandwidth, an optimal bandwidth for index $i$ can be obtained as the solution to the following maximization problem:

$$\hat{d}_i = \arg \max \{ \sum_{c \in C} \sharp M_c(d^i) - \sharp D_c(d^i) \}$$

In this paper, we allow the bandwidth to vary among countries by setting $d^i_c = f^i_c \times r_i$ (but $r_i$ is common for all countries), and choose an optimal $r_i$ in the same manner.
Subsequently, for all $c, \hat{c} \in C$ and $i \in I$, $f^i_c$ and $f^i_{\hat{c}}$ are regarded as equivalent if $|f^i_c - f^i_{\hat{c}}| \leq d^i_c$. In other words, if $|f^i_c - f^i_{\hat{c}}| \leq d^i_c$, then the development level of $c$ and that of $\hat{c}$ are regarded as indifferent. In the next section, we present the ranking result obtained through this procedure and compared with the result of the standard dominance order ranking.

3 Ranking Results and a Simulation Exercise

3.1 Results of the ranking methods

In this section, we show the ranking results obtained through the dominance order ranking and the extended ranking. We adopt the data used to calculate the HDI, which is one of the most consulted multidimensional poverty measures. The HDI is a composite index consisting of four indicators; life expectancy at birth, the adult literacy rate, the combined gross enrolment ratio for primary, secondary and tertiary schools, and GDP per capita. The data of these indicators for 182 countries were used to calculate the HDI in 2009.

Using this HDI 2009 data, we show two ranking results generated by the ranking methodologies proposed in the previous section, namely, the dominance order ranking and the extended dominance order ranking (See Table 1). Concerning the extended ranking, the calculated result of the optimal value of $r$ is 0.1073. While the HDI ranking in 2009 for 182 countries is a complete ranking from the first (Norway) to the 182nd (Niger), a number of countries are ranked identically in terms of both the dominance order ranking and the extended dominance order ranking. Consequently, the former manages to rank the 182...
countries into only seventeen groups from first to last place. In this ranking, twenty-two
countries are ranked into the top bracket (the rank of 69, namely the seventh place group)
and at the least, a country (the rank of 182nd, namely the bottom place group). While the
latter still sees several countries ranked the same, it succeeds in decreasing the numbers.
The extended ranking ranks 182 countries to forty groups. Only nine countries are ranked
at the top (the rank of 9th, namely the second place group) and at the opposite end,
a country (the rank of 181st and 182nd, namely the bottom and next group). In other
words, the extended ranking succeeds to improve the practical utility in the sense that it
alleviates the coarseness of the original dominance order ranking.

As stated in the previous section, this extension brings both benefit and cost to
the original ranking. The benefit is the fact that neglecting of slight difference among
data values possibly changes some binary relations non-comparable to comparable. Con-
versely, the cost of this neglect also possibly changes some binary relations from com-
parable to indifferent. For an example of the former case, see the Czech Republic and
Albania ranked 43rd in the dominance order ranking. The level of multidimensional
poverty of the former is \( f^i_{CR} \in I = (76.4, 99.0, 83.4, 24144) \) while that of the latter
is \( f^i_{ALB} \in I = (76.5, 99.0, 67.8, 7041) \). These countries are ranked the same due to
only a slight (0.1) difference in the value of life expectancy. The introduction of band-
width will mean this slight difference can be neglected, while the ranks of these countries
in extended ranking are quite different from each other (34th and 93rd). Likewise, for
an instance of the latter, see Portugal ranked 34th in the dominance order ranking with
\((f_{POR}^i)_{i \in I} = (78.6, 94.9, 88.8, 22765)\) dominates Chez Republic so that the former is ranked prior to the latter. Meanwhile, the introduction of bandwidth changes the binary relation on these countries from comparable to indifferent. Consequently, the ranks of these countries are the same (34th) in the extended ranking.

Our results shows that when we allow approximately a 10% difference in data value, the practical utility of the dominance order ranking is maximized, namely, the number of countries that have the same rank is minimized. It seems natural that we assume the existence of measurement error in any dataset. In particular, it is difficult to collect precise datasets in developing countries. With this in mind, acceptance of an error range of plus or minus 10% does not seem a quite unreasonable assumption.

### 3.2 A Simulation Exercise

As mentioned earlier, our extension has a secondary effect, whereby the extended method of ranking is more robust to measurement errors than the original method. To see this, a simulation exercise is implemented.

First of all, we assume that \(\ln f_c^i = \mu_c^i + \epsilon_c^i\), rather than the true value \(\mu_c^i\), is observed, where \(\epsilon_c^i\) is a random error. The random error may come from the measurement or other resources, and has i.i.d. \(N(0, \sigma_c^2)\). Hence, we regard \(f_c^i\) as a log-normal random variable with mean \(\exp(\mu_c^i + \sigma_c^2/2)\) and variance \(\exp(2\mu_c^i + \sigma_c^2)\{\exp(\sigma_c^2) - 1\}\).

We now consider the following measure \(\rho\) that indicates the extent to which the true value \(\mu_c^i\) explains the observed value \(\ln f_c^i\): \(\rho = \frac{E[\mu_c^i - \bar{\mu}]^2}{E[\ln f_c^i - \bar{\mu}]^2}\). This measure, which is similar
to the coefficient of determination (regression $R^2$) when regressing $\ln f_{i_c}^i$ on $\mu_{i_c}^i$, ranges between zero and one, and as it assumes a larger value, the error $\epsilon_{i_c}^i$ has less influence on the observed value $\ln f_{i_c}^i$. Subsequently, an unbiased and consistent estimator of $\sigma_i^2$ for each $\rho$ is calculated by:

$$\hat{\sigma}_i^2 = \frac{\sum (\ln f_{i_c}^i - \mu_{i_c}^i)^2}{N} = \frac{\sum [(\ln f_{i_c}^i - \bar{\mu}) - (\mu_{i_c}^i - \bar{\mu})]^2}{N} = \frac{(1 - \rho) \sum (\ln f_{i_c}^i - \bar{\mu})^2}{N}, \forall i \in I \text{ and } \forall \rho$$

Using this $\hat{\sigma}_i^2$, we simulate 100 runs of a (hypothetical) true value of $f_{i_c}^i$, denoted by $z_{i_c}^i$:

$$z_{i_c,t}^i = \exp \left( \mu_{i_c,t}^i + \frac{\hat{\sigma}_i^2 + \hat{\sigma}_i^2}{2} \right) = \exp \left\{ (\ln f_{i_c}^i - \epsilon_{i_c,t}^i + \frac{\hat{\sigma}_i^2 + \hat{\sigma}_i^2}{2} \right\} = f_{i_c}^i \times \exp (-\epsilon_{i_c,t}^i + \frac{\hat{\sigma}_i^2 + \hat{\sigma}_i^2}{2}),$$

where the additional subscript $t$ means the $t$-th trial, and $\epsilon_{i_c,t}^i$ is drawn at random from $N(0, \hat{\sigma}_i^2 + \hat{\sigma}_i^2)$. In each trial, using the hypothetical data $z_{i_c}^i$, we obtain ranking results based on the standard procedure and our ‘with-bandwidth’ procedure, and investigate the extent to which ranking results are sensitive to hypothetical (measurement) errors.

Figure 2 shows the results of the simulation exercise. As a measure to indicate the robustness of the ranking results, we employ the Spearman’s and the Kendall’s rank correlation coefficients between the ranking result, using the actual data and hypothetical data respectively. As the coefficients are close to unity, the results are interpreted as being robust to measurement errors. The figure shows that the coefficients of the extended method are significantly bigger than those of the original method, which indicates that our ‘with-bandwidth’ method is more robust to measurement errors than the original ranking method.
4 Conclusion

This paper proposed a ranking named the dominance order ranking, which is a method for ranking the levels of multidimensional poverty and extended it in order to improve its practical utility. This extended ranking is much finer than the original ranking. In addition, the extended ranking is more robust to measurement errors than the original.

While the dominance order ranking succeeds in eliminating some implicit arbitrariness in existing multidimensional poverty rankings, it has the disadvantage of a number of objectives being ranked the same. In other words, a number of objectives remain non-comparable. Due to this disadvantage, the dominance order ranking is criticized as lacking practical utility.

To enhance the practical utility, we introduce a new aspect that allows a certain range of measurement error in the data we use. Neglecting a slight disparity in the data value possibly decreases the number of countries with the same rank. We select the range of measurement errors that maximizes practical utility in the sense of minimizing the number of countries with the same rank. When we allow a difference of approximately 10.73% among data values, the practical utility is maximized and the number of ranks in ranking increased to forty from seventeen. This extension also enhanced the robustness to error in data and is shown by a simulation exercise.
Acknowledgement

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References


Table 1: Dominance Order Ranking, Extend Dominance Order Ranking and Human Development Index

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Note: The table contains placeholder data as the text is not legible.
Figure 1: Illustrative drawing of the dominance order ranking method

A: Comparable and non-comparable areas

Note: y and x on the vertical and horizontal axes are indicators representing the level of poverty, and capital letters A to H indicate countries. The shaded areas in both panels are ‘non-comparable areas’ of country D, and the area bounded by the solid line in the second panel is referred to as ‘indifference area’ of D.
Figure 2: Results of a simulation exercise

Note: Correlation coefficients are on the vertical axis, and $\rho$, which indicates the influence of the hypothetical error, is on the horizontal axis. Simulations are implemented at 0.01 unit intervals for $\rho \in [0.9, 0.99]$. 