Soc Indic Res (2014) 116:647–658
DOI 10.1007/s11205-013-0285-z

Does Human Development Index Provide Rational Development Rankings? Evidence from Efficiency Rankings in Super Efficiency Model

Po-Chin Wu · Chiung-Wen Fan · Sheng-Chieh Pan

Accepted: 25 February 2013 / Published online: 4 March 2013

Abstract The human development index (HDI) rankings have provided a referenced measure for people to choose a country in which to travel or live. This paper employs a superefficiency model to evaluate the rationality of the HDI rankings of 19 evaluated OECD countries in 2009. Compared to the HDI rankings, the efficiency rankings measured by the super-efficiency model have the following two advantages: (1) they consider the inputs that are used to generate the indicators for constructing the HDI, and decide the weights of inputs and outputs endogenously; (2) the input slacks measured by the super-efficiency model can evaluate whether the inputs are over-used and provide the improvement path of each country's input variables. Empirical result shows that approximately 75 % of the evaluated countries had rather different results in the efficiency rankings and the HDI rankings. Additionally, the input slack shows that roughly 70 % of sample countries over-used their capital per labor relative to their existing outputs (or the HDI).

Keywords Human development index (HDI) · Super-efficiency model · Input slacks · Over-used

1 Introduction

Traditionally, per capita income is frequently used as a measure of a country's economic development. However, the per capita income cannot fully reflect the development level of

P.-C. Wu (✉)
Department of International Business, Chung Yuan Christian University, No. 200, Chung Pei Rd., Chung Li 320, Taiwan, ROC
e-mail: pochin@cycu.edu.tw

C.-W. Fan
Department of Tourism and Leisure Management, Taoyuan Innovation Institute of Technology, No. 414, Sec. 3, Jhongshan E. Rd., Jhongli City, Taiwan, ROC

S.-C. Pan
Department of Leisure and Recreation Management, China University of Technology, 530, Sec. 3, Jhongshan Rd., Hukou Township, Hsinchu, Hsinchu County, Taiwan, ROC

a country, because it ignores the welfare of society and human being. To overcome this problem, the United Nations Development Programme (UNDP) proposed the human development index (HDI) for evaluating a country's achievements in life quality and human resource development in 1990. Essentially, the HDI is constructed by considering three dimensions—health, education, and standard of living, which are measured by life expectancy at birth, adult literacy rate and the combined primary, secondary, and tertiary gross enrollment ratio, and per capita income, respectively (see, for example, Desai 1991; McGillivray 1991; Anand and Sen 1994; NÜbler 1995; Sagar and Najam 1998; Sen 2000; Alkire 2002). Compared to per capita income, the HDI further considers the indicators associated with the physical quality—health and education, and demonstrates the change from economic development to socio-economic development.[1] In other words, the HDI is a more comprehensive measure than per capita income in assessing a country's development.

In fact, the HDI rankings published annually have provided a referenced measure for people to choose the country for living (see, for example, Musai and Ghorbani 2008; UNDP 2008; Musai et al. 2011). It also makes an indirect appeal for economists, socialists, politicians, and researchers to pay more attention to the question regarding how to utilize human resources efficiently for further improving human development. However, in constructing the HDI there are at least three ignored problems: (1) the HDI only synthesizes three sub-indices into a single index and ignores the problem of considering the inputs that generate the sub-indices in each evaluated country; (2) the methods synthesizing the three sub-indices into a single index are subjective and changeable, and are short of objective empirical support (see, for example, NÜbler 1995; Sagar and Najam 1998; Ogwang 2000). For example, in constructing the HDI, the variables—life expectancy at birth, educational attainment, and per capita GDP—were given equal weights before 2010. Since 2010 the UNDP has used the geometric mean of three normalized sub-indices—life expectancy index, education index, and income index-to construct the HDI. Adopting either equal weights method or geometric mean approach is still a subjective specification and neglects the relative importance among the normalized indices for each evaluated countries; (3) the HDI cannot tell the policymakers and researchers about whether the inputs, for example labor and capital, generating the normalized sub-indices are over-used. In other words, the countries in the HDI rankings may over-use their inputs that derive the three normalized sub-indices and the HDI rankings. This problem is especially important for the UNDP to highlight the efficiency of resource usage. Thus, employing an appropriate approach to overcome the above three problems and to provide complementary information for the HDI and HDI rankings is required.

Data envelopment analysis (DEA) is a well-known linear programming approach for evaluating the relative efficiency of a given set of similar decision making units (DMUs). This approach has the following advantages: (1) it is unnecessary to specify functional form for the relationship between inputs and outputs; (2) it could deal with the situation with multiple inputs and outputs and decide the weights of inputs and outputs endogenously; and (3) it could measure various kinds of efficiency scores and input and output slacks, which makes it possible to conduct a comprehensive evaluation of achievements. Thus, the applications of DEA approaches are widespread, covering the fields such as manufacturing, finance, education, and nonprofit organization (see, for example, Banker et al. 1986; Andersen and Petersen 1993; Steinmann and Zweifel 2003; Zelenyuk and Zheka 2006).

[1] The considerations of health and education in the HDI satisfy the propositions of Becker (1964) and Blaug (1976) that the utilization of human capital and education play important actors in a country's development.

The first and second advantages of DEA model can solve the first two problems occurred in constructing the HDI. That is, in measuring efficiency scores and the rankings of the evaluated countries by employing DEA model, the inputs are considered and the weights of inputs and outputs are determined endogenously.[2] More importantly, the input slacks measured from DEA model provide a useful information for evaluating whether the inputs of each evaluated country are over-used relative to their existing normalized indices (regarded here as the outputs in DEA models). This advantage can resolve the third problem derived from the construction of the HDI. Thus, DEA model is a proper candidate approach for researchers to resolve the problems confronted by the calculation of HDI.

While traditional DEA models (for example, BCC and CCR models) can measure various kinds of efficiency scores, they do not allow for the rankings of the efficiency units. Andersen and Petersen (1993) then propose a super-efficiency model to overcome this deficiency. Super-efficiency scores always benchmark a target DMU based on the efficiency of its peers regardless of its own efficiency level. In addition, super-efficiency scores can avoid a limited-value response variable in second-stage regression, as argued by Coelli et al. (2005). Thus, this paper first employs a super-efficiency model to evaluate the relative efficiency of the evaluated countries, and then compares the efficiency rankings with the HDI rankings. In addition, we can further assess whether the inputs in each evaluated country are over-used through the input slack(s) obtained from the super-efficiency model, which is ignored in building the HDI. Overall, the aim of this paper is two-fold: first, to provide complementary information for the HDI rankings by employing a super-efficiency model; and second, in light of the estimated efficiency scores and input slack(s) in the super-efficiency model, to suggest the path of improving the usage efficiency of input resources. Notably, our purpose is not to build a new HDI; rather, to employ a super-efficiency model for checking the rationality of the existing HDI rankings based on more reasonable conditions which are ignored in constructing the HDI, including the considerations of specific inputs used to generate the three sub-indices in HDI and endogenously determined weights associated with inputs and outputs across DMUs.

To verify our arguments mentioned above, we need first to conduct a super-efficiency model. This paper takes 19 OECD countries that had the top 30 rankings of HDI in 2009 as example.[3] In addition, we select two primary inputs-labor and capital, and three indicators used for constructing the HDI-life expectancy at birth, average number of years of schooling, and per capita income—as outputs.[4] A further explanation of the choices in DMUs, inputs, and outputs is provided in Sects 2 and 3. The empirical results show that the efficiency rankings measured by the super-efficiency model were rather different from the HDI rankings. In addition, the input slack reports that approximately 70 % (=13/19) of sample countries over-used their capital per labor relative to their existing outputs (i.e., the three sub-indices in the HDI). Clearly, the evaluation results of the super-efficiency model can provide some useful information as a complementary tool for the supporters of the HDI to evaluate a country's development.

The remainder of this paper is organized as follows. In Sect. 2, we briefly introduce the building of HDI and review the literature on the topics related to HDI and DEA models. Section 3 briefly introduces the input-oriented super-efficiency model used to evaluate the

[2] Even though there are weight constraints in DEA models, the optimal weights of inputs and outputs are also determined endogenously.

[3] The use of the HDI is to rank countries or regions by level of human development: low, medium, and high.

[4] This paper abandons the other indicator used for constructing the HDI-literacy rate, because the rates have no prominent difference among the 19 sample countries.

rationality of HDI rankings. Section 4 presents the data source and empirical results, and Sect. 5 draws conclusions.

2 Literature Review

Human development index (HDI) has become one of the most widely used indicators for comparisons of welfare, which is linked to its grounding in multidimensional well-being measurement as well as to its simplicity. A HDI is constructed by considering three dimensions—health, education, and standard of living, which are measured by life expectancy index, education index, and income index, respectively. The UNDP claims that social welfare is better evaluated by using HDI, not (real) per capita GDP, since the latter only reflects average income. However, there also have been some criticisms on HDI.[5] For example, Gormely (1995) argues that the choice of per capita income will influence HDI and its rankings. Wolff et al. (2009) and Taner et al. (2010) have empirically suggested that the countries have been misclassified by the HDI. In addition, Panigrahi and Sivramkrishna (2002), Osberg and Sharpe (2003), Cherchye et al. (2008), and Grimm et al. (2008) present their concerns with the problems in HDI rankings. In brief, most previous studies have attempted to build a more justifiable HDI.

As mentioned in the Introduction, the major aim of this paper is not to construct a new HDI; rather, to investigate the rationality of the existing HDI rankings by considering specific inputs used to generate three sub-indices—income index, education index, and life expectancy index—in HDI. To achieve this goal, employing a DEA model is a feasible method. The basic DEA model, named CCR, is proposed by Charnes et al. (1978) and has opened up a new nonparametric scheme for the measurement of production-based efficiency. In the basic DEA framework, DMUs are regarded as decisional entities responsible for converting multiple inputs to outputs. Another version of the basic DEA model frequently used is the Banker et al. (1986) model, BCC. The BCC version is more flexible and allows variable returns to scale; consequently, it measures only pure technical efficiency for each DMU. Since then, the basic DEA models have been extensively applied and extended to measure the performance of various kinds of DMUs (Banker et al. 1986; Andersen and Petersen 1993; Steinmann and Zweifel 2003; Zelenyuk and Zheka 2006).[6]

Data envelopment analysis (DEA) approach is unnecessary to specify a functional form for the relationship between multiple inputs and multiple outputs and can measure various efficiency scores, which makes it possible to perform a comprehensive evaluation of achievements (Pan et al. 2011). That is, in performing efficiency rankings by using DEA models, researchers simultaneously consider multiple inputs and outputs, while the multiple inputs are ignored in evaluating HDI rankings. Besides, the users of HDI employ an equal weights method or a geometric mean method to integrate the three sub-indices (i.e., income index, education index, and life expectancy index) into a value of HDI. This treatment ignores the relative importance of each sub-index in forming HDI. Contrarily, in determining the efficiency scores of DMUs, DEA models consider the relative efficiency among DMUs; endogenously construct a non-linearly arranged set of best practice countries and determine the weights associated with inputs and outputs. These weights are allowed to vary thereby accounting for cross-sectional heterogeneity.

[5] For more details on the criticisms on HDI, see Kovacevic (2011).

[6] Tavares (2002) and Emrouznejad et al. (2008) provide a comprehensive bibliography of methodological and application aspects of DEA.

Regarding the application of DEA on HDI issues, Mahlberg and Obersteiner (2001) re-measure the HDI by employing DEA models. They use the CCR model and the DEA model with weight restrictions developed by Allen et al. (1997) to compare performance in a multiple output setting. Employing a DEA-like linear programming model to evaluate the relative human development of countries, Despotis (2005a, b) and Lozano and Gutiérrez (2008) generate a new development index to evaluate social and economic development. Other researches such as Raab and Habib (2007) and Malul et al. (2009) apply DEA approach to describe and compare the development efficiency of countries using the variables such as GNP, distribution of national income, Gini index, and environmental performance. Ülengin et al. (2011) employ a super-efficiency model and artificial neural networks to improve the original HDI. They incorporate the key factors for competitiveness of each country as the input items of DEA model, including basic requirements, efficiency enhancers, and innovation and sophistication factors. However, the focus of these studies still rests on the way of improving HDI to make the comparison of countries' social development more justifiable. Most importantly, employing DEA models to assess the efficiency rankings of DMUs also can investigate whether resource inputs are efficient corresponding to the existing outputs (i.e., the three sub-indices for forming HDI) and provide the information about the source of inefficient inputs from the evaluated input slack(s), which is completely ignored by the previous studies (Mahlberg and Obersteiner 2001; Despotis 2005a, b; Raab and Habib 2007; Lozano and Gutiérrez 2008; and Malul et al. 2009). In summary, DEA approach is an appropriate instrument to evaluate the rationality of HDI rankings and can provide useful information for improving the efficient use of resources in the evaluated DMUs.

In fact, in evaluating the efficiency scores of specific groups of DMUs, the basic DEA models (i.e., CCR and BCC models) cannot distinguish the rankings of the DMUs on the efficient frontier (i.e., the efficient DMUs), which makes the comparison between HDI rankings and the efficiency rankings of DEA model impossible. However, a super-efficiency model can overcome this problem. The super-efficiency model, proposed by Andersen and Petersen (1993), executes the basic DEA models, but it does so under the assumption that the DMU being evaluated is excluded from the reference set. This allows a DMU to be located above the efficiency frontier, i.e., to be super-efficient. In other words, this procedure allows for more effective ranking of efficient units, while the scores for inefficient DMUs remain the same as in the basic DEA models (Zhu 1996; Pan et al. 2011). However, the previous studies (Mahlberg and Obersteiner 2001; Despotis 2005a, b; Raab and Habib 2007; Lozano and Gutiérrez 2008) have neglected the rankings of efficient DMUs, which would cause biased calculations of input and output slacks, efficiency scores, and usage efficiency of resource.

In executing the performance evaluation of DMUs by employing DEA models, the numbers of inputs, outputs, and DMUs play a core role in influencing the evaluated efficiency scores, which in turn affect the rankings of efficiency. This paper employs the super-efficiency model to assess the rationality of HDI rankings based on the same sample DMUs (i.e., the 19 OECD countries) and same outputs variables (i.e., the three sub-indices—income index, education index, and life expectancy index); therefore, the choice of proper inputs is critical.[7] Al-Shammari (1999) empirically assesses the relative efficiency of fifty-five Jordanian manufacturing companies listed in the Amman Financial Market for the year 1995. The number of employees, paid-in capital, and fixed assets are three input measures used for the study. Mostafa (2007) uses two inputs: assets and

[7] While Ülengin et al. (2011) employ super-efficiency model and artificial neural networks to improve the original HDI, the inputs (e.g., efficiency enhancers, and innovation and sophistication factors) used in their super-efficiency model are more likely to be classified as outputs, not inputs.

employees and three outputs: net profit, market capitalization, and share price to measure the relative market efficiency of sixty-two top listed companies in Egypt. In addition, in evaluating the efficiency of local governments, Pan et al. (2011) use capital and labor as two main input factors. They also illustrate the necessary adjustments in the slack variables for achieving Pareto efficiency. Evidently, labor and capital are two important input variables frequently used in the super-efficiency models.

Overall, the present paper employs a super-efficiency model to empirically investigate whether the efficiency rankings of the selected 19 OECD countries provide a more reasonable conclusion than the HDI rankings. To execute the super-efficiency model, we use two inputs (i.e., labor and capital), and three outputs (i.e., life expectancy index, education index, and income index) used for building a HDI. We will further explain the choice of inputs and outputs in the next section. From the calculated efficiency rankings of the super-efficiency model, one could compare them with HDI rankings; calculate the weights (or importance) of inputs and outputs in different DMUs; and analyze the source of inefficient usage of inputs corresponding to the existing three sub-indices (i.e., the outputs in the super-efficiency model) which form the HDI. Notably, the latter two functions are completely ignored in the process of constructing a HDI. In summary, the evaluation result of the super-efficiency model provides another thinking about welfare rankings of HDI by considering more reasonable conditions.

3 Model

3.1 Human Development Index

Human development index (HDI) is constructed by considering three dimensions: life expectancy at birth, knowledge and education, and standard of living. The formulas for calculating HDI are different between the period 1990–2010 and the period after 2010. The sample DMUs used in this paper are the 19 selected OECD countries in 2009; therefore, we briefly introduce the formula used for calculating HDI before 2010, named the old method. The old method used for calculating HDI includes three sub-indices: longevity index (LI), measured by life expectancy at birth; educational attainment index (EAI), measured by a combination of adult literacy (two-thirds weighting) and combined (i.e. primary, secondary, and tertiary) enrolment (one-third weighting) ratios; and standard of living, measured by real per capita GDP (GDPI). To calibrate the dimensions, UNDP has assigned minimum and maximum values for each underlying sub-index. Performance in each sub-index is then calculated and expressed as a value between 0 and 1. According to UNDP's approach, these three sub-indices are assigned equal weightings as follows:[8]

$$HDI = (LI + EAI + GDPI)/3 \tag{1}$$

3.2 Super-efficiency Model

A DEA model evaluates the performance of a set of DMUs, $\{DMU_j, j = 1, 2,\ldots,n\}$, which produce multiple outputs by using multiple inputs. As mentioned above, there are 19 evaluated OECD countries using specific inputs to create their performance of

[8] Even for the new method developed for calculating HDI after 2010, the HDI is constructed by geometric mean of the three normalized indices.

development; therefore, n = 19. Each DMU_j has a set of s output measures,y_{rj},.$r = 1$, 2,…,s, and a set of m input measures, x_{ij}, $i = 1, 2, \ldots m$. DEA identifies an efficient frontier where all DMUs have a unity score. Empirically, there may be DMUs which have this efficient frontier; therefore, ranking frontier DMUs is very important in the DEA model. Super-efficiency models can be used for ranking the performance of efficient DMUs. When a DMU under evaluation is not included in the reference set of the original DEA model, the resulting DEA model is called super-efficiency model. The super-efficiency scores of an input-oriented DEA model with constant return to scale (CRS) are derived from the following linear programming model:[9]

$$\underset{\theta_o, \lambda, s_i^-, s_r^+}{Min} \quad \theta_o^* = \theta_o - \varepsilon \left(\sum\nolimits_{i=1}^{m} s_i^- + \sum\nolimits_{r=1}^{s} s_r^+ \right) \tag{2}$$

$$\begin{aligned} s.t \quad & \sum\nolimits_{j=1, j \neq o}^{n} \lambda_j x_{ij} + s_i^- = \theta_o x_{io} \quad i = 1, 2, \ldots, m \\ & \sum\nolimits_{j=1, j \neq o}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1, 2, \ldots, s \\ & s_i^-, \; s_r^+ \geq 0 \\ & \lambda_j \geq 0 \quad j \neq o \quad j = 1, 2, \ldots, n \end{aligned}$$

where the derived efficiency score θ_o^* specifies the optimal super-efficiency ofDMU_o, revealing that the effective utilization degree of inputs relative to outputs. x_{io} and y_{ro} are the i-th input and r-th output for a DMU_o under evaluation, respectively. x_{ij} and y_{rj} are the i-th input and r-th output of DMU_j, respectively. λ_j is the weight given to DMU_j in its efforts to dominate DMU_o, $j = 1,2,\ldots,n$. Clearly, λ_j is endogenously determined by the DEA model and is obviously different from the weights (i.e., 1/3) used to construct the HDI in Eq. (1). $s_i^-$and $s_r^+$are input and output slack variables, respectively. An output slack means that for a given set of inputs a DMU has failed to produce the expected output level relative to the DMU's peers on the efficiency frontier. Besides, an input slack indicates that a DMU has used an excessive amount of input to produce a given level of output relative to its efficient peers. ε is a non-Archimedean infinitesimal.

The solution to model (2) is interpreted as the largest contraction in inputs of DMU_o that can be carried out, given that DMU_o will be excluded from reference technology. The first two restrictions in model (2) form the convex reference technology; the third restriction restricts the input slack s_i^- and output slack s_r^+variables to be non-negative; and the last restriction limits the weights (or intensity variables) to be non-negative. The procedures of solving super-efficiency score include: first, to exclude the DMU_o from sample data, and then using the remaining data to construct a new efficient frontier. Second, based on the new constructed efficient frontier and the excluded DMU_o, one can recalculate the super-efficiency score. That is, in running each of these linear programs, the reference set involves $(n-1)$ DMUs. By solving model (2) n times, one can get relative efficiency for all the DMUs. Notably, for the inefficient DMU in the CCR model, its super-efficiency score is the same as the efficiency value in the CCR model (see Charnes et al. 1978). Zhu (1996) indicates that the input-oriented CRS super-efficiency model is always feasible unless certain patterns of zero data entries are present in the inputs. Because the data used in this paper are positive, then model (2) is always feasible. In an input-oriented DEA model, the value of θ_o^* ranges in the interval (1, ∞) for the DMUs identified as efficient, with larger

[9] For more details on the utility of super-efficiency model, see Andersen and Petersen (1993).

values indicating increasing efficiency. Contrarily, θ_o^* ranges in the interval (0, 1) for the DMUs identified as inefficient, with smaller values indicating decreasing efficiency. Empirically, the super-efficiency model is conducted by employing EMS (efficiency measurement system) 1.3 provided by Scheel (2000).

4 Empirical Results

4.1 Selection of Variables

The DMUs used in the present paper are the OECD countries that had the top 30 rankings of the HDI in 2009.[10] After the exclusion of the countries with incomplete data, we have 19 OECD countries selected, including Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, South Korea, Netherlands, New Zealand, Spain, Sweden, Switzerland, UK, and US.[11] In addition, in performing the super-efficiency model, the inputs and outputs are selected as follows:

4.1.1 Inputs

Production factors mainly include capital, labor, land, and entrepreneurship. For a country, its executive power serves as an appropriate proxy variable for entrepreneurship and is embedded in its operating performance. The executive domain of a government, a proxy variable for land, is less variable; therefore, it is exogenous to the government. Thus, the inputs we choose to evaluate the efficiency of countries primarily focus on labor and capital (see Mostafa 2007; Pan et al. 2011).[12] Labor and capital are measured by labor force and capital services, respectively, and are integrated into an input ratio—capital per labor for simplifying the analysis in super-efficiency model. The capital per labor (also called capital-labor ratio) is formed by dividing capital by labor and is generally used to measure a country's degree of capital intensity. Jorgenson (2009) states that capital-intensity societies tend to have a higher standard of living over the long run.

4.1.2 Outputs

To have the same basis for comparison, we choose three indices used for constructing the HDI as output variables—life expectancy at birth, average number of years of schooling, and per capita GDP. Data sets come from the OECD database and the World databank.

[10] While the UNDP has used a new method to measure the HDI since 2011, the latest data sets are available in 2009.

[11] We have tried to search the missing data from other dataset or the statistical data of individual countries; however, the result is disappointed. In addition, some previous studies employing OECD countries as sample objects to conduct relative empirical analysis have also faced the problem of missing data (e.g., Dreger and Reimers 2005; Baltagi and Moscone 2010). We appreciate the suggestion of one anonymous reviewer.

[12] As mentioned early above, our main aim is not to cover complete inputs and outputs in the super-efficiency model. Thus, we choose only two crucial inputs in the super-efficiency model.

Table 1 Rankings of the HDI and super-efficiency scores in 2009

Country	Original HDI rankings	Revised HDI rankings[a]	Super-efficiency score	Super-efficiency ranking	Super-efficiency input slack
Australia	2	1	1.0000	3	0.00
Austria	14	11	0.7731	14	2625.53
Belgium	17	14	0.6763	19	4,043.22
Canada	4	2	0.7641	15	2,674.14
Denmark	16	13	0.6791	18	4,406.44
Finland	12	9	0.7526	16	2,799.34
France	8	6	0.9526	7	507.138
Germany	22	18	0.8376	10	1,616.56
Ireland	5	3	1.0000	3	0.00
Italy	18	15	1.0001	2	0.00
Japan	10	8	1.0000	3	0.00
South Korea	26	19	0.8300	11	1,410.33
Netherlands	6	4	0.8904	9	1,148.55
New Zealand	20	16	1.7213	1	0.00
Spain	15	12	0.9229	8	752.863
Sweden	7	5	0.7454	17	3,200.44
Switzerland	9	7	1.0000	3	0.00
UK	21	17	0.7746	13	2,469.91
US	13	10	0.7942	12	2,949.61

[a] Means that we re-rank the rankings of HDI only based on the selected 19 countries in the first two columns

4.2 Empirical Results

Table 1 reports the rankings of the HDI and the efficiency scores in super-efficiency model. The countries that had similar rankings in the super-efficiency scores and the HDI include Australia, Austria, France, Ireland, and the US (about 25 % of the sample countries). However, the remaining fourteen countries had apparently different rankings between the super-efficiency scores and the HDI. For the countries—New Zealand, Italy, Germany, and South Korea, their rankings in super-efficiency scores were evidently superior to the HDI. Contrarily, for the countries—Canada, Sweden, and Finland, the rankings of super-efficiency scores were noticeably inferior to the HDI. That is, once considering the input (i.e., capital per labor) and the relative efficiency among the evaluated countries, the HDI over-estimated the rankings of Canada, Sweden, and Finland, and under-estimated the rankings of New Zealand, Italy, Germany, and South Korea.

In addition to comparing the rankings of the HDI and super-efficiency scores, the measured input slack in the super-efficiency model can provide useful information for a country to improve the efficiency of resource usage relative to its existing outputs. Clearly, only six countries—Australia, Ireland, Italy, Japan, New Zealand, and Switzerland—had zero input slack, revealing that their inputs—capital per labor—had reached optimal utilization relative to the remaining evaluated countries. In other words, the remaining 13 countries had experienced the situation of over-using capital per labor relative to their existing outputs (i.e., the HDI and HDI rankings).

If we consider efficiency scores and input slacks simultaneously, the countries—New Zealand, Italy, Australia, Ireland, Switzerland, and Japan—achieved top six rankings. Except for New Zealand and Italy, the remaining four countries (about 20 % of the sample countries) had similar rankings to the HDI. In addition, few of the countries that had relative top rankings in the HDI, such as Canada and Sweden, did not utilize their inputs efficiently from the viewpoint of super-efficiency model. Similarly, few of the countries that had relative low rankings in the HDI, such as Italy and New Zealand, had utilized their inputs efficiently.

5 Conclusions

The HDI is a comprehensively referenced index for people to select a country in which to live. However, in constructing the HDI, there are at least three problems should be resolved: (1) the weights and mechanism used to synthesize three normalized indices into a single index are still ambiguous and subjective; (2) the role of the inputs used to generate the three normalized indices is ignored; (3) whether the inputs are over-used relative to the HDI has not yet been investigated. This paper employs a super-efficiency model to resolve these problems.

A super-efficiency model integrates multiple inputs and multiple outputs of each evaluated country into a relative efficiency score. The multiple outputs used in this paper are the three normalized indices for constructing the HDI, and the multiple inputs is simplified as an input ratio—capital per labor. The empirical result shows that 75 % of the 19 evaluated OECD countries had efficiency rankings significantly different from the HDI rankings. The evaluated OECD countries with top rankings in the HDI, e.g., Canada and Sweden, had approximately the worst rankings in the super-efficiency scores. Contrarily, the evaluated OECD countries with low rankings in the HDI, e.g., New Zealand and Italy, had the top 2 rankings in the super-efficiency scores. In addition, the input slack indicates that about two-thirds of the evaluated countries over-used their inputs (i.e., the capital per labor here) relative to their outputs (i.e., the HDI).

Our empirical results have the following three policy implications. First, this paper provides the efficiency rankings measured by the super-efficiency model with identical outputs used in the HDI rankings and two extra inputs, which can serve as a complementary instrument for evaluating a country's development under the considerations of the usage efficiency of inputs and relative operating efficiency among the evaluated countries. Second, in addition to publishing the HDI annually, the announcement of the usage efficiency of the inputs that are used to generate the HDI is also important. The input slacks measured from a super-efficiency model can be used to assess whether the evaluated countries have used their resources to generate the HDI efficiently, and provide the paths for improving the usage efficiency of resources. Third, to obtain more accurate efficiency rankings and the information with respect to resources usage efficiency, the questions regarding what kinds of inputs need to be put into the super-efficiency model and whether all the evaluated countries in the HDI are the evaluated DMUs in the super-efficiency model need to be resolved.

References

Alkire, S. (2002). Dimensions of human development. *World Development, 30*(2), 181–205.

Allen, R., Athanassopoulos, A., Dyson, R., & Thanassoulis, E. (1997). Weight restrictions and value judgments in data envelopment analysis: evolution, development and future directions. *Annals of Operations Research, 73*, 13–34.

Al-Shammari, M. (1999). A multi-criteria data envelopment analysis model for measuring the productive efficiency of hospitals. *International Journal of Operations & Production Management, 19*(9), 879–897.
Anand, S., & Sen, A. (1994). *Human development index: Methodology and measurement*. New York: UNDP.
Andersen, P., & Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science, 39*, 1261–1264.
Baltagi, B. H., & Moscone, F. (2010). Health care expenditure and income in the OECD reconsidered: Evidence from panel data. *Economic Modelling, 27*(4), 804–811.
Banker, R. D., Conrad, R. F., & Strauss, R. P. (1986). A comparative application of data envelopment analysis and translog methods: An illustrative study of hospital production. *Management Science, 32*, 30–44.
Becker, G. S. (1964). *Human capital*. New York: Columbia University Press.
Blaug, M. (1976). *An introduction to the economics of education*. Harmondsworth: Penguin.
Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *Europe Journal of Operational Research, 2*, 429–444.
Cherchye, L., Ooghe, E., & Van Puyenbroeck, T. (2008). Robust human development rankings. *Journal of Economic Inequality, 6*(4), 287–321.
Coelli, T. J., Rao, D. S., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Berlin: Springer.
Desai, M. (1991). Human development: Concepts and measures. *European Economic Review, 35*, 350–357.
Despotis, D. K. (2005a). Measuring human development via data envelopment analysis: The case of Asia and the Pacific. *Omega, 33*(5), 385–390.
Despotis, D. K. (2005b). A reassessment of the human development index via data envelopment analysis. *Journal of the Operational Research Society, 56*, 969–980.
Dreger, C., & Reimers, H. E. (2005). Health care expenditures in OECD countries: A panel unit root and cointegration analysis. *International Journal of Applied Econometrics and Quantitative Studies, 2*(2), 5–20.
Emrouznejad, A., Barnett, R. P., & Tavares, G. T. (2008). Evaluation of research in efficiency and productivity: A survey analysis of the first 30 years of scholarly literature in DEA. *Socio-Economic Planning Sciences, 42*(3), 151–157.
Gormely, P. J. (1995). The human development index in 1994: Impact of income on country rank. *Journal of Economic and Social Measurement, 21*, 253–267.
Grimm, M., Harttgen, K., Misselhorn, M., & Klasen, S. (2008). A human development index by income groups. *World Development, 36*(12), 2527–2546.
Jorgenson, D. (2009). *The economics of productivity. An Elgar reference collection*. Cheltenham: UK.
Kovacevic, M. (2011). *Review of HDI critiques and potential improvements* (p. 33). UNDP: Human Development Research Paper.
Lozano, S., & Gutiérrez, E. (2008). Data envelopment analysis of the human development index. *International Journal of Society Systems Science, 1*(2), 132–150.
Mahlberg, B., & Obersteiner, M. (2001). *Remeasuring the HDI by data envelopment analysis. Interim report, IR-01-069*. Laxenburg, Austria: International Institute for Applied Systems Analysis (IIASA).
Malul, M., Hadad, Y., & Ben-Yair, A. (2009). Measuring and ranking of economic, environmental and social efficiency of countries. *International Journal of Social Economics, 36*, 832–843.
McGillivray, M. (1991). The human development index: Yet another redundant composite development indicator? *World Development, 19*(10), 1461–1468.
Mostafa, M. M. (2007). Evaluating the comparative market efficiency of top listed companies in Egypt. *Journal of Economic Studies, 34*(5), 430–452.
Musai, M., & Ghorbani, P. (2008). *Effect of factors affecting demand for inbound tourist travel to Iran after the Islamic Revolution until 2004. Proceedings of the National Conference on Investment in Tourism Development*. Tehran: Tarbiat Modarres University.
Musai, M., Mehrara, M., Nemati, S. F., & Tak, M. N. (2011). Demand for travel to Iran and human development index. *European Journal of Social Sciences, 25*(1), 14–20.
NÜbler, I. (1995). The human development index revisited. *Intereconomics Review of European Economic Policy, 30*(4), 171–176.
Ogwang, T. (2000). Inter-country inequality in human development indicators. *Applied Economics Letters, 7*(7), 443–446.
Osberg, L., & Sharpe, A. (2003). *Human well-being and economic well-being: What values are implicit in current indices? Centre for the study of living standards research report, 04*. Ottowa: Centre for the Study of Living Standards.

Pan, S. C., Liu, S. Y., Peng, C. J., & Wu, P. C. (2011). Local governments' efficiency evaluation: Consideration of undesirable outputs and super-efficiency. *African Journal of Business Management, 5*(12), 4746–4754.

Panigrahi, R., & Sivramkrishna, S. (2002). An adjusted human development index: Robust country rankings with respect to the choice of fixed maximum and minimum indicator values. *Journal of Human Development, 3*(2), 301–311.

Raab, R., & Habib, E. (2007). A productivity growth accounting approach to the ranking of developing and developed nations. *The International Journal of Accounting, 42*, 396–415.

Sagar, A. D., & Najam, A. (1998). The human development index: A critical review. *Ecological Economics, 25*, 249–264.

Scheel, H. (2000). EMS: Efficiency measurement system user's manual. Version 1.3.

Sen, A. (2000). A decade of human development. *Journal of Human Development, 1*(1), 17–23.

Steinmann, L., & Zweifel, P. (2003). On the (in)efficiency of Swiss hospitals. *Applied Economics, 35*(3), 361–370.

Taner, M. T., Sezen, B., Alpkan, L., & Aren, S. (2010). *Recomputation of UNDP's HDI rankings by data envelopment analysis*. St. Petersburg, Russia: International Strategic Management Conference.

Tavares, G. (2002). A bibliography of data envelopment analysis (1978–2001). *Rutcor Research Report,* RRR 01–02, January.

Ülengin, F., Kabak, Ö., Önsel, S., Aktas, E., & Parker, B. R. (2011). The competitiveness of nations and implications for human development. *Socio-Economic Planning Sciences, 45*(1), 16–27.

UNDP (United Nations Development Program). (2008). Human development reports, http://hdr.undp.org/en/humandev/.

Wolff, H., Chong, H., & Auffhammer, M. (2009). *Human development index: Are developing countries misclassified?*. Milwaukee, Wisconsin: Agricultural and Applied Economics Association Annual Meeting.

Zelenyuk, V., & Zheka, V. (2006). Corporate governance and firm's efficiency: The case of a transitional country Ukraine. *Journal of Productivity Analysis, 25*(1–2), 143–157.

Zhu, J. (1996). DEA/AR analysis of the 1988–1989 performance of the Nanjing Textile Corporation. *Annals of Operation Research, 66*, 311–335.