

CROSS EVALUATION OF THE ICT-DEVELOPMENT INDEX

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ABSTRACT

The Information and Communication Technology Index (ICT-index) continues to grow worldwide. The various dynamics in ICTs have typically become a major driving force for competitiveness, productivity, superposition of resources at both international and national level, and in collaboration. However, the ICTs do not measure the progress countries are making towards becoming information societies. The ICT-Development Index (IDI) was introduced to measure ICT developments of countries worldwide. It is a composite index made up of 11 indicators covering ICT access, use and skills. This paper introduces an innovative cross evaluation based on Data Envelopment Analysis model as alternative approach to measure the IDI; the novel characteristic of this cross efficiency approach is that unique optimal weights are determined for each country under evaluation such as the variation of weights is minimized; statistical analysis shows that the generated IDI scores are highly significant when compared with the IDIs reported by the International Telecommunication Union (ITU). Furthermore, this cross efficiency method alleviates the weak discrimination of the classical DEA models when assigning rankings to efficient decision making units.

Keywords: Information Society, Information Communication Technology, ICT index, ICT development index, Cross Efficiency, Data Envelopment Analysis.

Introduction

The strong link between the spread of Information Communication Technology (ICT) and socio-economic development was noted by the declaration of principles at the World Summit on the Information Society and first intruded ICT Development Index (IDI) in the 2009 edition of Measuring Information Society (ITU 2010b). In this study, we present an innovative cross evaluation DEA-based model to measure the ICT- IDI of major countries. The model is innovative because it considers only outputs defined as performance measures by the ITU. Furthermore, cross efficiency scores are obtained for each country based on the determination of unique optimal weights which preserve the efficiency scores defined by the classical DEA models. The cross efficiency method alleviates the weak discrimination of the classical DEA models when assigning rankings to efficient decision making units, providing insightful information for decision makers.

ICT can be used as a powerful tool in creating jobs, generating economic growth, increasing productivity, and increasing international cooperation in trade, Foreign Direct Investment, finance and others. The increased demand for ICT in both global and domestic markets has been propagated by the expansion and growth of online transactions, e-business, and e-government. The integration of ICT into these fields will improve the infrastructure in developing countries including industries, organizations, and the communication system as a whole through strengthening their competitive capacities in the global markets and enhancing the overall economic performance (Emrouznejad, Cabanda, & Gholami, 2010).

There are multiple positive effects that are involved in the results from managing the transition towards an information society that include the core components of information society, communication technologies, and information. The various dynamics in ICT have typically become a major driving force for competitiveness, productivity, superposition of resources at both international and national level, and collaboration (Hanaftzadeh, Saghaei & Hanaftzadeh, 2009).

ICT has brought an overall prosperity, growth, and development in many countries and regions. Many developing countries have integrated ICT as a key component in their education system. At the moment, the education system in almost every country cannot be effective without the integration of ICT. The investment in ICT by many countries has been proved by many literature reviews to have a positive impact on the economy of countries including the developing ones (Lee, Gholami, & Tong, 2005), investing in ICT has contributed to economic growth and development in many developed countries, but does not apply to most developing countries. This is because most developing countries have the casualty of investing in ICT while the developed countries have the casualty of having growth in ICT (Piotti and Macome, 2007).

Related Research

In the developed countries, much research has been done to discover what goes wrong in the attempt to grasp what factors that are constraining the integration of ICT in many fields such as education, governments, organizations, and industries (Groff and Mouza, 2008) distinguished between critical factors in their framework of addressing challenges involved in the use of

technology in classrooms. Investment in ICT has got positive impact in the growth in developed countries as supported by many previous studies. Lee and colleagues (Lee, Gholami, & Tong, 2005) also evidenced that investment in ICT contributes to growth in economy in many developed countries and the newly industrialized economies. The neoclassical growth model was applied by Jalava and Pohjola (2002) in order to understand the contribution of ICT in 39 countries in the period of 1980-1995.

Gust and Marquez (2004) propose an interesting hypothesis to explain the productivity divergence among the industrial countries. The hypothesis links regulatory environments and ICT adaptation where countries with the huge protection in employment have the least ICT adaptation and the smallest growth in productivity. They verified this hypothesis when they estimated two linear regressions with a panel of 13 industrial countries independently using data from the 1990s. Daveri (2002) did explore on growth accounting in 14 European Union countries and the U.S to measure the contribution of ICT investment on economic growth. The EU countries showed a little difference to America in regards to ICT adoption (Shirazi, Ngwenyama & Morawczynski, 2010).

The major driving force development of most economies is recognized to be information and communication technology. However, there are no clear indicators of how technology has contributed a great deal to the overall economic growth of developing countries when compared to developed countries. A study done by Kraemer and Dedrick (2001) shows that because a developing country such as South Africa is short of knowledge and capital investment, it will lag far behind the developed nations in its development of ICT industry and proliferation. The developing countries face many problems of handling the relationship between economic strategies and ICT promotion. Wong (2002) in his study shows that it is practically impossible to repel the implementation of ICT in the globalized markets. Many researchers including Steinmueller and Bastos (1995), Wong (2002) and Hanaftzadeh, et al., (2009) referenced that ICT is very valuable source as for information in production, export, and import on the global basis.

Methodology

Data Envelopment Analysis (DEA) was first introduced by A. Charnes, W. W. Cooper and E. Rhodes (1978), who describe such analysis as a non-parametric technique that uses linear programming to construct a piece-wise linear production frontier based on observed best practice as an approach to measure efficiency of every one units of decision involved. There has been an increase in the development of the concept and utilization of DEA to measure the relative efficiency of production from small setting as productive units to entire countries. DEA is mostly undertaken with absolute numerical data, which reflects the size of the units of observations among the others. DEA models can therefore be precise reflecting the variables or constant to scale as suit the underlying knowledge and technology of the relationship between the inputs and outputs.

The concept of DEA has been interpreted as the relationship of how fluctuating data in a linear dimension can be captured over top of the observed scattered data, as Seiford and Thrall (1990) described. That is, DEA modeling identifies an efficient surface that projects the elements as an

enveloping surface. The projection path to the envelope surface is determined by whether the model is output-oriented or input-oriented depending upon the relationship among the factors involved and objective that is considered as part of the data.

Flexibility is one advantage of this approach and no assumptions are made in regards to the underlying technology, the functional form, or the distribution of errors. The ability of DEA to deal with multiple inputs and multiple outputs is a very important feature. DEA yields an indicator of efficiency, calculated for each unit, defined as the ratio of the weighted sum of its output of the weighted sum of its inputs. The weights are thus calculated within the implied mathematical model. The weights are derived from the efficiency frontier, comparing a unit with other units that produces similar outputs and using similar inputs. The technique chooses the set which yields the unit with the highest efficiency score since there are an unbound number of sets of weights which would satisfy this (Seo, Lee, and Oh , 2009).

There can be the reformulation of the functional mathematical model by constraining the numerator or the denominator of the efficiency ratio to be equal to one. This recognizes that through mixing a ratio it is the relative values of the numerator and the denominator that are crucial and not their absolute values. The major problem then becomes either maximize weighted output with weighted input equal to one or minimize weighted input with output equal to one. Some others, on a similar approach, rather than employing absolute numbers, often employ ratios as indicators of inputs and outputs (Peeraer and Petegem, 2011).

Among the many application of DEA is CCR modeling (Charnes, Cooper and Rhodes, 1978), which is the systematic assembly of indices. A systematic property of CCR is that it can apply constant return to scale, which changes the implicit assumption of the decision making units (DMU) operating at a fixed scale. Such property yields the opportunity to observe how the DMU can fluctuate according to their levels of efficiency. A DMU represents the entity under evaluation; in this research a DMU represents a country. Each DMU has an associated set of inputs and outputs respectively, which represent multiple performance measures. Consider a set of n DMUs, each DMU_j ($j = 1, \dots, n$) consumes m inputs x_{ij} ($i = 1, 2, \dots, m$) for producing s outputs y_{rj} ($r = 1, 2, \dots, s$). The relative efficiency of a particular DMU_o is defined as a ratio of the weighted sum of outputs to the weighted sum of inputs and is obtained by solving the following fractional programming problem:

$$\begin{aligned} & \max \frac{\sum_{r=1}^s u_r y_{r0}}{\sum_{i=1}^m v_i x_{i0}} \\ \text{s.t.} & \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1, \quad j = 1, 2, \dots, n \\ & u_r \geq 0, \quad r = 1, 2, \dots, s \\ & v_i \geq 0, \quad i = 1, 2, \dots, m \end{aligned} \tag{1}$$

where u_r is the weight given to the r th output and v_i the weight given to the i th input. The fractional program can be converted into a linear programming problem which has the following dual formulation (2):

$$\begin{aligned}
 & \min \theta_0 \\
 \text{s.t.} & \\
 & \sum_{j=1}^n \lambda_j x_{ij} \leq \theta_0 x_{i0}, \quad i = 1, 2, \dots, m \\
 & \sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, \quad r = 1, 2, \dots, s \\
 & \lambda_j \geq 0, \quad j = 1, 2, \dots, n
 \end{aligned} \tag{2}$$

where λ_j ($j = 1, \dots, n$) are nonnegative scalars and θ_0 is the efficiency of DMU_0 , the DMU under evaluation. Model (2) is known as the CCR model and is an input oriented model with constant returns to scale assumption.

The solution of model (2) assigns the value of 1 to all efficient DMUs making difficult to differentiate among all efficient DMUs. Several approaches have been proposed for differentiating DMUs when there are more than one efficient DMU. A common approach is the so called super efficiency DEA model introduced by Andersen and Petersen (1993). This method enables efficient DMUs to achieve an efficiency score greater than one facilitating the assignment of rankings to all efficient DMUs.

An extension of DEA is the cross efficiency method which was developed for identifying the best performing DMUs and for ranking DMUs using cross efficiency scores. The advantage of the cross efficiency method is that alleviates the weak discrimination of the classical DEA model. The cross efficiency method has two steps. In the first step, the classical efficiency scores are determined using model (2). A set of optimal weights preserving the efficiency values for each DMU is determined in the second step, and these weights are used for calculating the peer evaluation score θ_{pj} of DMU_j ($j=1, \dots, n$) using the weights obtained by DMU_p (3).

$$\theta_{pj} = \frac{\sum_{r=1}^s u_{rp} y_{rj}}{\sum_{i=1}^m v_{ip} x_{ij}} \quad j = 1, \dots, n \tag{3}$$

In general, there are multiple solutions when determining the optimal weights for the efficiency scores generated by model (2). Some model suggestions have been suggested for reducing this undesirable case. Sexton et al. (1986) and Doyle and Green (1994) have proposed the so-called aggressive efficiency model aimed to minimize the efficiencies of other DMUs while preserving the efficiency of the DMU under evaluation. Recently Bal and Örkücü (2008) developed a model which minimizes the variation of weights and obtains a unique optimal set of weights.

The DEA model which preserves the efficiency scores defines by model (3) and minimizes de coefficient of variations is model (4).

$$\min \frac{\sqrt{\frac{\sum_{r=1}^s (u_r - \bar{u})^2}{s-1}}}{\bar{u}} + \frac{\sqrt{\frac{\sum_{i=1}^m (v_i - \bar{v})^2}{m-1}}}{\bar{v}}$$

s.t.

$$\sum_{r=1}^s u_r y_{rp} = \theta_p,$$

$$\sum_{i=1}^m v_i x_{ip} = 1,$$

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0, \quad j = 1, 2, \dots, n$$

$$u_r \geq 0, \quad r = 1, 2, \dots, s$$

$$v_i \geq 0, \quad i = 1, 2, \dots, m$$

(4)

After solving model (4), a set of optimal weights are defined for each DMU and peer evaluation scores can be determined using (3). Once all peer evaluations scores are calculated, each DMU has n cross efficiency scores. The cross efficiency score CE_j for each specific DMU_j is determined by calculating its corresponding mean of cross efficiency scores (5).

$$CE_j = \frac{\sum_{k=1}^n \theta_{kj}}{n} \quad j = 1, \dots, n$$

(5)

Data Indicators and Measurements

As specified in the report ITU 2010d the IDI is a combined index conformed of three sub-indices, including 11 indicators. The selection of indicators was based on data availability and quality and the relevance of a particular indicator for contributing to the main objectives and conceptual framework of the IDI. The IDI obtained by ITU 2010d were based on a fixed distributed weight for the indexes considered. Table 1 summarizes such indicators and their sub-indices with their distribution of weights.

In a related preceding study (Emrouznejad et al., 2010) the data used was based on the set of indicators with the number of economies, as reported in the ITU 2007d (183 country economies and 4 indices and a total of 10 sub-indices). However the ITU 2010d indices and countries have shifted three indices, discarding the one for intensity, and to 153 economies. Moreover, the current arrangement of indicators are based on the definition and interpretation of the indices to the estimation of IDI, but mainly because the number of affiliated economies in given period of time and, perhaps, the stipulation of the ITU committee in charge of defending the parameters

involved to determine IDI indices. This research totally differs from the study of Emrouznejad et al. (2010) in the sense that a novel cross efficiency DEA approach based on unique optimal weights is presented for obtaining the ICT index.

The factors under the ITU framework include the ones associated to the gross enrolment rates as part of the description of the indicator of skills. The different level of education describes an interaction of students and teachers which they considered as school level factors, and factors that are inherent to technology itself. Mumtaz (2000) distinguished three interlocking factors: resources, institution, and teachers. Drent & Meelissen (2008) categorizes these factors into what cannot be manipulated and those that can be manipulated. Important contextual factors at school level include the socio-cultural setting of a school and other structural characteristics such as school type, ICT infrastructure, and government ICT policy. At the teacher level, there are two types of common barriers, the first-order or eternal barriers like lack of technical support or limited resources, and second-order or internal barriers like the attitude of teacher in ICT (Peeraer et al., 2011). As part of this study gross enrolment rate is represented by the indicator of secondary enrolment, as alteration from the study done by Emrouznejad et al. (2010).

Table 1: ICT Development Index: indicators and weights				
ICT access		Ref. Value	(%)	Weight
1	Main (fixed) telephone lines per 100 inhabitants.	60	20	40
2	Mobile cellular subscriptions per 100 inhabitants.	170	20	
3	International Internet bandwidth Bit/s per Internet user	*100,000	20	
4	Proportion of households with computer	100	20	
5	Proportion of households with internet	100	20	
ICT use		Ref. Value	(%)	Weight
6	Internet users per 100 inhabitants	100	33	40
7	Fixed broadband Internet subscribers per 100 inhabitants	60	33	
8	Mobile broadband subscriptions per 100 inhabitants	100	33	
ICT skills		Ref. Value	(%)	Weight
9	Secondary Gross enrolment ratio	100	33	20
10	Tertiary Gross enrolment ratio	100	33	
11	Adult literacy rate	100	33	

* This corresponds to a log value of 5, which was used in the normalization step.

Source: ITU 2010d.

The actual parameters (access, use and skill) as estimated by the ITU and the descriptive statistics of such indicators are summarized in table 2. From where it can be noticed the dispersion among the ICT indicators along the economies considered. Particuarly in regards

access indicators, just as an example, reporting a standard deviation of over 900,000, and identifying Cuba and as the nation with the lowest International Internet bandwidth Bit/sec. per Internet user and Luxembourg on the upper bound. In a positive course Cuba is reported as the nation with the highest index value under the gross enrolment and adult literacy rate, as 73.66 and 5.28 units above the overall reported average, respectively. Such divergence on the factors considered to estimate the take an important trait into the estimation of the IDI.

Results

The super efficiency DEA and the DEA cross efficiency were evaluated using indicators as reported in the ITU 2010d and re-rank used in the stage of cross evaluation. The rank values of the different countries reported in the study as IDI from ITU 2010d and IDI using DEA and the cross ICT development indexes are being contracted in table 3.

Additionally, to strengthen our findings, we tested the two different arranged groups of economies; we compared the set of IDI ranked according cross-efficiency DEA against the set of data from original reported in the ITU 2010d. We use Spearman's rank correlation test. The parameters observed in the test were $S = 11374$, $p\text{-value} < 2.2e-16$. Such indicators not only show an excellent fitting on the two data sets but also support the premise of validation of the alternative approach.

Observing the rho coefficient as additional indicator to the alternative non-parametric approach, it can be hypothesized a correlation among the original ranking against the proposed approach ranking. An initial claim will expect a linear correlation among the two figures, the one initially reported and the one approached by using cross-efficiency. The test statistic to observe, in this case, is the true value of rho. Since the reported rho sample statistic is 0.8445 it can be claimed that there is significant positive linear correlation among the two different rankings.

For the correlation, the hypothesis that will drive our tests statistics is whether the linear model estimated is statistically significant. If there is a significant linear relationship between the IDI ranked as in the ITU 2010d (independent variable) and the IDI ranked using cross-efficiency DEA (dependent variable), the slope will not equal zero. So, our null hypothesis is defined as: $H_0: \beta = 0$ and alternative one: $H_a: \beta \neq 0$. The null hypothesis states that the slope is equal to zero, and the alternative hypothesis states that the slope is not equal to zero. Given a p-value of $2.2e-16$ we reject the null hypothesis.

In conclusion, we observe p-values for the coefficient of slope lower than alpha (α) level of 0.05; we reject the null hypothesis with enough power. It can be claimed that there is not significant difference in the ranking reported by the ITU 2010d and the ones estimated using cross efficiency DEA methodology.

Table 3: Country's IDI ranked as un and the ITU 2010d, DEA IDI and Cross ICT IDI estimations

Economy DMU	ITU 2010d Rank	DEA IDI Rank	X-Efficiency		Economy DMU	ITU 2010d Rank	DEA IDI Rank	X-Efficiency	
			Rank	Scores				Rank	Scores
Sweden	1	6	1	0.9952	Uruguay	51	50	52	0.9169
Luxembourg	2	1	2	0.9894	Cyprus	52	39	41	0.9164
Korea (Rep.)	3	2	3	0.9894	Romania	53	44	43	0.9157
Denmark	4	13	4	0.9876	Montenegro	54	47	96	0.9128
Netherlands	5	17	5	0.9873	Belarus	55	26	25	0.9073
Iceland	6	10	6	0.9828	Argentina	55	49	64	0.9057
Switzerland	7	14	7	0.9812	Mongolia	56	95	48	0.9018
Japan	8	15	8	0.9752	Israel	57	27	63	0.8991
Norway	9	24	9	0.9738	Ukraine	58	27	75	0.8982
United Kingdom	10	30	10	0.9736	TFYR Macedonia	58	51	31	0.8978
Hong Kong, China	11	8	11	0.9729	Trinidad & Tobago	59	47	53	0.8936
Finland	12	12	12	0.9708	Serbia	59	53	70	0.8913
Germany	13	18	13	0.9699	Maldives	60	68	26	0.8903
Singapore	14	50	14	0.9688	Chile	62	54	87	0.8888
Australia	15	4	15	0.9655	St. Vincent and the Grenadines	63	46	69	0.8884
New Zealand	16	23	16	0.9628	Costa Rica	64	70	30	0.8879
Austria	17	37	17	0.9592	Fkuwa	65	31	29	0.8879
France	18	25	18	0.9583	Brunei Darussalam	66	42	56	0.8777
United States	19	38	19	0.9567	Portugal	67	32	71	0.8777
Ireland	20	31	20	0.9562	Venezuela	68	61	68	0.8774
Canada	21	32	21	0.9509	Kazakhstan	69	29	84	0.8758
Estonia	22	7	59	0.9507	Fiji	69	91	79	0.8758
Belgium	23	40	23	0.9495	Kuwait	71	65	32	0.8680
Macao, China	24	16	24	0.9493	Thailand	72	76	82	0.8670
Spain	25	49	40	0.9412	Viet Nam	73	86	62	0.8584
Slovenia	26	20	74	0.9410	Philippines	76	90	76	0.8518
Italy	28	19	27	0.9405	China	77	79	85	0.8451
United Arab Emirates	29	5	42	0.9351	Mexico	78	77	92	0.8379
Greece	30	9	22	0.9347	Colombia	79	63	88	0.8352
Bahrain	33	11	36	0.9344	Georgia	80	36	73	0.8246
Hungary	34	45	81	0.9299	Seychelles	80	66	33	0.8245
Lithuania	35	22	34	0.9289	Azerbaijan	81	35	37	0.8089
Czech Republic	37	43	58	0.9280	Malaysia	81	56	39	0.0000
Slovak Republic	38	42	35	0.9241	Jordan	82	74	45	0.0000
Poland	40	39	28	0.9236	Brazil	83	60	50	0.0000
Latvia	41	21	93	0.9235	Peru	85	75	54	0.0000
Bulgaria	43	48	60	0.9208	Turkey	87	57	61	0.0000
Russia	48	33	49	0.9174	Mauritius	89	72	72	0.0000

Conclusions

With this study we advanced on the approach on assessing ICT on international level using cross efficiency DEA methodology. The proposed cross efficiency DEA model is an excellent alternative approach for measuring the IDI. It has the advantage that no weights are defined by the user, they are appropriately assigned by the model, furthermore the proposed model identifies the unique optimal weights which maximize efficiency and minimize variation between them.

The cross efficiency method alleviates the weak discrimination of the classical DEA models when assigning rankings to efficient decision making units and the countries are ranked based on their performance in each indicator. The results proved to be highly significant with the reported by the ITU. This approach has superior theoretical and empirical implications than the predecessor approaches. Such advance in the application of the methodology represents a significant operationalization of the way measurement of digital advancement and a supplement to the current ITU's index methodologies.

Important implications of this study are in the global policy making, as the empirical indications are supporting the effective capability of making global ICT policies and efforts towards global ICT development issues. (Emrouznejad et al., 2010) Administration in the different economies could determine their actual condition in the global ICT, as it can be benchmarked using the recommend instrument, and have a stronger stipulation of their own efforts towards competitive development. Along the same line, a general recommendation, based on the empirical results, to achieve an advanced ICT, especially in developing countries in the lower boundaries of the ranking of ICT indexes should consider an a more aggressive and strategic impulse on their advancement on their ICT core infrastructure.

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