PRODUCTIVITY ANALYSIS OF THE TELECOMMUNICATION SECTOR IN INDIA

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Abstract- **This paper applies the data envelopment analysis (DEA) approach to measure the Productivity performance of India's telecommunications sector. This study applies a data envelopment analysis (DEA) approach to measure the magnitude of performance differences between leading telecom operators in terms of their marketability and Profitability. It compares the financial valuations and relative productivity efficiencies of the leading global telecoms. Empirical results indicate that none of the telecoms with high valuations are highly efficient in terms of DEA, and that wireless operators are more efficient than full-service telecoms in terms of profitability and marketability. The results are expected to be utilized as benchmarking strategies for wireless and full-service telecommunications to be equipped with competitive advantages.**

Keywords*- *Productivity analysis, Efficiency Measurement, Total Factor Productivity, Data Envelopment Analysis, CCR Model, BCC Model.

I. INTRODUCTION

Telecommunication is rapidly changing the way people communicate with each other and organizations conduct businesses around the world. Among policymakers, telecommunications may be viewed as a strategic resource. A well developed telecommunication infrastructure attracts investments, because the cost of doing business is reduced significantly in such environment. Telecommunications may also cause firms to be more productive and perform at lower cost. From an economic perspective, the role of telecommunications in development can be considered an important factor of production. Survival in highly competitive telecommunications markets requires the firms to focus on operating efficiency as the basis for competitive advantage [1-3]. The measures or indicators of the efficiency of a firm can in turn be determined by its performance measurement. Wen-Min Lu [1].

Waves of regulatory changes in the telecommunication industry frequently lead new business strategies for telecommunication companies, or "telecoms." New regulations or business models associated with mobile virtual network operators (MVNO), resale, and indirect access (IA) have increased competition from the global and regional alliances formed by telecom operators in the fixed-line, wireless, and full-service markets Jungnam An [2].

Wireless mobile communication is a burgeoning area of the telecommunication industry due to technical advances and increasing market demand. Additional market growth is still expected in the upcoming years. The market potential and opportunities have brought about severe competition among service providers. Intense competition has driven the need for increased network coverage and the enhancement of capabilities to meet market demand Boong Kwon [3].

A well-developed telecommunications system plays a key role in the economic growth and development of a country. The performance and development of the telecommunications sector are related to the structure of the industry. After privatization and liberalization, the performance of the telecommunications industry in many countries has improved remarkably. Prices have gone down and productivity has increased. Despite the significant expansion of India's telecommunications sector over the last few years, there has been a lack of quantitative studies on the productivity performance of the telecommunications sector in India. The main objective of this paper is to measure the productivity performance of India's telecommunications sector at the provincial level. The data envelopment analysis (DEA) approach is used in the productivity measurement. The nonparametric DEA approach is applied to measure relative efficiency and input slacks (i.e. redundancies and unproductive inputs used in production) in the telecommunications sector at the provincial level.

II. PRODUCTIVITY STUDIES OF TELECOMMUNICATIONS

Since the early 1980s, there has been a growing interest in measuring the productivity and efficiency of the telecommunications sector. In the early period, the focus was on measuring total factor productivity (TFP) growth, which is the growth in output not accounted for by the growth in inputs. Since the privatization and deregulation of the telecommunications sectors in the 1980s, a number of studies have been conducted to evaluate the efficiency and productivity differences before and after the reform. Increase in efficiency and productivity in the post-reform period was confirmed by most of the studies.

More recently, production frontier approaches such as DEA and the Malmquist index have become popular in measuring the efficiency and productivity performance of the telecommunications industry Lam [4]. Productivity is just the ratio of output to input. Productivity changes due to differences in production technology, differences in the efficiency of the production process, and differences in the environment in which production takes place. The ability to include efficiency change as a component of productivity change depends on the data that are available and on the assumptions that must be made. A credible assessment of the role of efficiency change in productivity change requires a pooling of cross-sectional and time-series data.

In the analysis designed to measure productive efficiency, there are two commonly used approaches the econometric approach and the data envelopment analysis approach._ The econometric approach to incorporating efficiency change into a model of productivity growth is due to Bauer [5]. The approach begins with a cross-sectional translog cost function and a system of input share equations with technical and allocative inefficiency allowed. Technical change is incorporated into the specification by adding time as an argument in the cost function and the share equations. The computational burden, however, is great. In theory the specification does allow productivity change as rejected by a change in the cost function to occur as a result of scale economies, technical change, and changes in technical and allocative efficiency. Shin and Ying [6] illustrate the use of this econometric approach in an application to the telecommunications industry.

An alternative approach to measuring productive efficiency is the mathematical programming approach known as data envelopment analysis (DEA). Drawing on the work of Debreu [7] and Koopmans [8], Farrell [9] argued that it is practical to measure productive efficiency based on a production possibility set consisting of the conical hull of input-output vectors. This framework was generalized to multiple outputs and reformulated as a mathematical programming problem by Charnes et al. [10]. The DEA approach does not require any assumptions about the functional form,
in contrast to the econometric approach.

III. RESEARCH METHODOLOGY

Data Envelopment Analysis is relatively a new data oriented approach for evaluating the performance of set of peer entities called Decision Making Units (DMU) which convert inputs to outputs. It is a popular benchmarking method; a multifactor productivity analysis model for measuring the relative efficiencies of a homogeneous set of DMUs. It is a nonparametric estimation approach for generating the efficiency frontier that is derived from the DMU. These DMU's may be hospitals, universities, schools, Air force wings, business firms etc. As this requires very few assumptions, DEA has also opened up possibilities for use in cases which have been resistant to other approaches because of the complex unknown nature of relations between the multiple inputs and multiple outputs involved in DMU's. DEA is an excellent and easily usable methodology for modeling operational processes for performance evaluations. DEA's empirical orientation and the absence of a need for the numerous priori assumptions that accompany other approaches have resulted in its use in a number of studies involving efficient frontier estimation in the governmental and nonprofit sector, in the regulated sector and in the private sector. The technique was suggested by Charnes, Cooper and Rhodes [10] and is built on the idea of Farrell.

To design an efficient firm the regulator must specify the production technology with which the service will be delivered, the price of inputs and the cost of assets involved. With all these presumed data, it is possible to define an efficient production frontier used as the comparison benchmark for the group of companies. The efficiency is measured using the ratio of aggregated output to the aggregated input. Following Charnes et al, a DMU is said to be efficient if it is not possible to increase (decrease) the level of output (input) without increasing the use of at least one other input or decreasing the generation of at least one other output. The DMU's that lie on the efficiency frontier are efficient in the DEA model. In contrast, the entities that do not lie on the efficiency frontier are regarded as inefficient. DEA is a linear programming method that can deal with multiple inputs and multiple outputs simultaneously, yet

DEA does not require the assignment of predetermined weights to the input and output factors. In this study, two DEA models were applied. CCR model developed by Charnes *et al* [10] and the BCC model developed by Banker [11]. In particular CCR model is the basic model which produces Constant Returns to Scale (CRS) efficiency frontier. The relative efficiency evaluated for the CCR model is the overall efficiency score and the efficiency of the DMU's are set to be lie between 0 and 1.

A. Production Function

1) The efficient frontier

The computations of the productive efficiency represent one of the most important topics in analyzing performance of firms, industry sector and the whole economy. Whatever is the level of the economic analysis the computation of the productive efficiency derives directly from the notion of production function. The production function indicates the maximum production level which can be obtained by different combinations of the production factors for a given technology. In its turn the production function in literature has been estimated both by mean of parametric technique, via regression analysis, and by mean of non parametric technique, via Data Envelopment Analysis (DEA). The former reflects "average" or "central tendency" behavior of the observations while the latter deals with best performance and evaluates all performances by deviation from the frontier line. To guide imagination in comparing the two above techniques consider figure 2 which represent, for explanatory reason, a constant production function for a single input *(x)* single output *(y)* case.

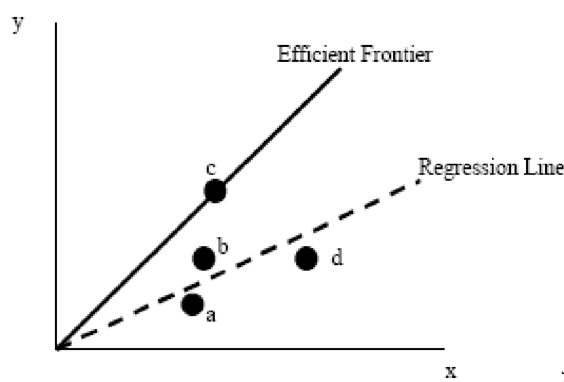

Figure 1. Regression Line vs Frontier Line

DEA identifies point like *c* for future examination or to serve as benchmark to use in seeking improvements. The efficient frontier touches at least one point and all points are therefore on or below this line. In fact, the name Data Envelopment Analysis come from this property because in mathematical term, such a frontier is said to "envelope" these points. The statistical approach, on the other hand averages *c* along with the other observations, including *d* as a basis for suggesting where improvements might be sought. So the two approaches can also result in different approaches to improvement. One of the advantages of the non parametric technique, based on linear programming, is that the a priori specification of the functional form is not required. In other terms, with linear programming, the efficiency of a productive unit will be established in comparison with the optimum, which is the situation of the "ideal" productive unit (in our example the "ideal" productive unit is represented by the projection of the points, below the efficient frontier, on the frontier itself) providing the maximum output with the least of input. Analogously it can be considering the dual problem that is identifying the "ideal" productive unit providing the most of output with the minimum input. In the literature can found different DEA model with respect to the type of envelopment surface and orientation. There are three types of envelopment surfaces associated with the assumption concerning returns-to-scale: Constant Returns to Scale (CRS), Variable Returns to Scale (VRS) and Non Increasing Return to Scale (NIRS). The CRS model assumes that there is a proportional growth between inputs and outputs. The VRS and the NIRS assume that the scale of operation affects the results.

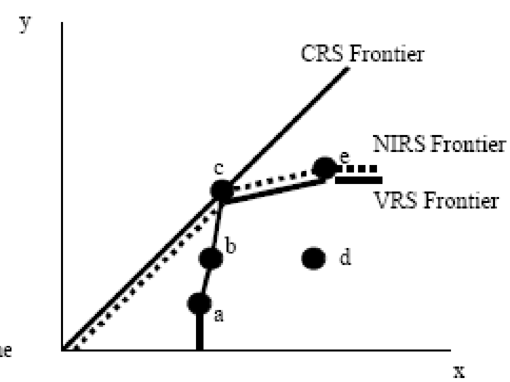

Figure 2. CRS ,VRS and NIRS Efficient Frontier.

In figure 2 are drawn the three types of frontier for the five productive unit which produce one output, *y*, with one input, *x*. Once that the frontier has been built the input efficient measure, in the sense used by Farrell (1957), is represented by the maximum reduction in inputs, given the outputs, which allows to reach the efficient frontier.

More formally, let us consider a set of *I* productive unit. Each productive unit *i (i=1,2,…, I)* produce *M* output, **m y** *(m=1,2,…, M)*, employing *N* inputs, **n x** *(n=1,2,…, N)*. So, if **Y** denotes the vector of output values and, **X** denotes the vector of inputs value then the mathematical expression of the CRS, model with input orientation is given by the following dual linear programs called the envelopment form (Coelli, 1996[12] and Lovell 1983[13] for mathematical details about the DEA models):

$$\begin{aligned} &\min_{\theta,\lambda} \theta \\ &st: -y_i + Y\lambda \ge 0, \\ &\theta x_i - X\lambda \ge 0,\ \lambda \ge 0 \end{aligned} \qquad i=1, n\ (1)$$

The value of obtained from the solution of relations (1) gives the Overall Technical Efficiency, O(i) , of unit i. Note that linear programming problem must be solved I times in each period t, once for each productive unit in the sample. A value of less than one of O (i) indicates overall technical inefficiency for productive unit i. The VRS and the NIRS models are obtained imposing $\sum_{i=1}^{I} \ddot{e}_i^t = 1$ and $\sum_{i=1}^{I} \ddot{e}_i^t \le 1$ in the minimization problem (1) respectively. By mean of the CRS and VRS models it is possible to decompose the Overall Technical Efficiency into its component, Scale Efficiency i S and Pure Technical Efficiency i P. In particular for each unit i the efficiency measure can be written as follow:

O (i) = **S (i)** × **P (i)** *i = 1, I* (2)

In other terms an overall technical inefficiency, **O(i)< 1**, for a productive unit can be caused by an inefficient input output configuration, **P (i)**<1 , and as well as the size of the operation **S(i)** <1 . Finally comparing the VRS results with the NIRS ones it can be individuate for each productive unit the type of returns to scale: increasing returns to scale (irs), constant return to scale (crs) and decreasing return to scale (drs).

2) Measuring the change of Total Factor Productivity

Once obtained the measure of efficiency for each productive unit in each period it is possible to compute the Malmquist (1953) [14] productivity index. The Malmquist productivity index allows changes in productivity to be broken down into changes in efficiency and technical change. Moreover, it can be estimated using DEA. Letting, in this framework, the analytical mathematical formulation apart (see Coelli, 1996[8] among others) the Total Factor Productivity TFP change for each productive unit can be written as follow:

M (i,t)= **OC(i,t)** ×**TC(i,t)** *i=1,…,I; t = 1,…,T* (3)

Where OC**(i,t)** measures the Overall Technical Change and t TC**(i,t)** measures the Technological Change between t and t+1. A value of t OC**(i,t)** greater than one indicates an efficiency improvement and a value of TC**(i,t)** higher than unity indicates technical progress. Moreover, from relation (2), the Malmquist index can be further decomposed taking into account the Scale Efficiency Change, t SC**(i,t)** , and Pure Technical Efficiency Change, t PC**(i,t)** :

M(i,t) = **SC(i,t)** × **PC(i,t)** ×**TC(i,t)** *i=1,…,I; t = 1,…,T* (4)

Values of the **M (i,t)** **PC(i,t)** , **SC(i,t)** or **TC(i,t)** greater than one indicate efficiency improvement or technological progress, while, on the contrary, values less than one indicate efficiency decline or technological regress Thus, if for productive unit *i* between period *t* and *t+1* technological change has not occurred, no movement of CRS efficient frontier (**TC (i,t) =1**), the variation of the TFP measured by the Malmquist index is due to the change of technical efficiency of the productive unit, **OC (i,t)** , which in its turn can be caused by scale, **SC (i,t)** , and/or pure technical,**PC(i,t)** movements.

On the contrary if the productive unit between period *t* and *t+1* has not change its own technical efficiency, **OC (i, t)** = 1 , the variation of TFP can be explained only by the movement of the CRS frontier. Clearly, in the most of cases, the variation of TFP is caused by both efficiency and frontier movements

B. Mathematical formulation of DEA models:

1) CCR Model

Let as assume that there are ***n*** DMUs to be evaluated. Each DMU consumes varying amounts of ***m*** different inputs to produce ***s*** different outputs. Specifically, ***DMU***j consumes X*rj* amounts of input i and produces Y*rj* amounts of output ***r***. As per the definition of relative efficiency, this is the ratio of weighted sums of outputs to weighted sums of inputs. In mathematical programming parlance, this ratio, which is to be maximized forms the objective function for the particular DMU with a set of normalizing constraints (one for each DMU) reflects that this ratio of every DMU, must be less than or equal to unity.

$$Max\, h_0(u,v) = \sum u_r y_{ro} \Big/ \sum v_i x_{io}$$

$$\text{Subject to} \quad \sum u_r y_{rj} \Big/ \sum v_i x_{ij} \le 1 \quad \text{for } j = 1,\dots,n$$

$$u_r, v_i \ge 0\ \forall\ i \text{ and } r.$$

where u_r and v_i are the weights of the input and output, y_{ro} , x_{io} are rth output and ith input of DMUo Using Charnes-Cooper transformation, transforming (u,v) to (μ,ν),

$$\text{Max } z = \sum_{r=1}^{s} \mu_r y_{ro}$$

Subject to

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_{ij} x_{ij} \leq 0$$

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

$$\mu_r, v_i \geq 0$$

For which the LP dual problem is

$$\theta^* = \min \theta$$

$$\text{Subject to } \sum_{j=1}^{n} x_{ij} \lambda_j \leq \theta x_{io} \qquad i = 1,2, \ldots m$$

$$\sum_{j=1}^{n} y_{rj} \lambda_j \geq y_{ro} \qquad r = 1,2, \ldots s$$

$$\lambda_j \geq 0 \qquad j = 1,2 \ldots n \qquad \theta \text{ unrestricted}$$

2) BCC Model

The BCC model produces a variable returns to scale (VRS) efficiency frontier and evaluates both technical efficiency and scale efficiency. Thus the overall efficiency can be decomposed into technical efficiency and scale efficiency. Technical efficiency is the efficiency of converting inputs to outputs, while scale efficiency recognizes that economy of scales will not obtain at all scales of production and there is only one Most Productive Scale Size (MPSS) where the scale efficiency is 100%. Therefore the DMU is said to be efficient if and only if it is both technical and scale efficient. Thus the dual DEA program for considering the VRS model is as follows

$$\text{Min } \theta_m$$

$$\text{Subject to } \quad Y\lambda \geq Y_m$$

$$X\lambda \leq \theta X_m \quad \text{and}$$

$$\sum_{n=1}^{N} \lambda_n = 1 \qquad \lambda \geq 0, \theta \text{ free}$$

In general, DEA programs incorporating the additional convexity constraint to take into account variable returns to scale are called BCC DEA model. The variable λ introduced into the convexity constraint also brings out the value of increasing or decreasing returns to scale.

If $\sum_{n=1}^{N} \lambda_n = 1$ then the reference DMU is expected to exhibit constant returns to scale.

If $\sum_{n=1}^{N} \lambda_n < 1$, then the reference DMU exhibits Increasing returns to scale and

If $\sum_{n=1}^{N} \lambda_n > 1$ then the reference DMU exhibits decreasing returns to scale.

3) Most Productive Scale Size

The CCR efficiency is the overall efficiency which also takes into account the scale efficiency. For the DMU which are scale inefficient, it is an indirect measure that they are not operating on the Most Productive Scale Size. If the present scale of operation of the DMU does not lead to 100% scale efficiency, then the scale size of every inefficient DMU to be operated will be identified by the calculation of MPSS. Identifying the Most Productive Scale Size is complex for any DMU when dealing with multiple inputs and multiple outputs. Banker has proved that MPSS for a given inefficient firm can be obtained using the following relationship.

$$\left(X_{i,m}^{MPSS}, Y_{i,m}^{MPSS}\right) = \left[\theta_m^* \frac{X_{im}}{\sum_{n=1}^{N} \lambda_{nm}^*}, \frac{Y_{jm}}{\sum_{n=1}^{N} \lambda_{nm}^*}\right]$$

IV. OPERATIONAL EFFICIENCY ANALYSIS

In this study, CCR model, with constant returns to scale (CRS) is applied to evaluate the overall efficiency. In addition, the BCC model, with variable returns to scale (VRS), is used to evaluate the technical and scale efficiencies. Both the dual linear programming formulations are run for every DMU. The combined results of the CCR model, BCC model, Peer units for the inefficient DMU and the Slacks in the Inputs are considered. The analysis of the slack variable shows the way for the improvement for the inefficient DMU. The input slack values represent the needed reductions of the corresponding input factors to become an efficient DMU. The BCC model is used to evaluate the technical efficiency and scale efficiency. Some of the DMUs which are inefficient in CCR model now become efficient in BCC model. The results of BCC model can show the major sources of inefficiencies among the all the operators and also provide possible directions of improvement for the overall efficiency for each utility. In the BCC model, four utilities which shown inefficiency in their CCR model became relatively efficient which modifies the frontier line.

V. CONCLUSIONS

The analysis has been conducted employing non parametric techniques, based on linear programming, and called Data Envelopment Analysis (DEA) which allows measuring the Malmquist Total Factor Productivity index. The CCR and BCC models combined produce technical efficiency, pure technical efficiency, and scale efficiency. On the basis of these three types of efficiencies, three major findings were obtained. This paper demonstrates that DEA is a useful tool to measure efficiency because the DEA model does not require an explicit form of the production function and can separate pure technical efficiency from scale efficiency. Pure technical efficiency is a measure of how a firm utilizes its resources under exogenous constraints In contrast, understanding scale efficiency particularly matters at a time when acquisitions among private sectors are prevalent and public sector privatization is promoted. By using DEA under models of both constant and variable returns-to-scale, the paper suggests that firms can improve scale efficiency through acquisitions but might encounter poor pure technical efficiency resulting from integrating resources of two existing units in the short run. The analysis has been conducted employing non parametric techniques, based on linear programming, and called Data Envelopment Analysis (DEA) which allows measuring the Malmquist Total Factor Productivity index.

VI. REFERENCES

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[1] Wen-Min Lu 1, Shiu-Wan Hung 2, and Chih-Jou Chen, Evaluating the Performance of Global Telecom Operators, Proceedings of the 2008 IEEE IEEM, 978-1-4244-2630-0/08/$25.00 ©2008 IEEE.

[2] Jungnam An, Productivity Analysis of Wireless and Full-service Telecommunications, 2007 International Conference on Convergence Information Technology, 0-7695-3038-9/07 $25.00 © 2007 IEEE.

[3] He-Boong Kwon, Philipp A. Stoeberl, Seong-Jong JooMeasuring comparative efficiencies and merger impacts of wireless communication companies, Benchmarking: An International Journal Vol. 15 No. 3, 2008 pp. 212-224.

[4] Pun-Lee Lam, Alice Shiu**,** Productivity analysis of the telecommunications sector in China, Telecommunications Policy 32 (2008) 559–571.

[5] P. Bauer, Decomposing TFP growth in the presence of cost ineffciency, non-constant returns to scale, and technological progress, Journal of Productivity Analysis,{ (1990)287}300.

[6] R. Shin, J. Ying, Costly gains to breaking up: LECs and the baby bells, Review of Economics and Statistics 98 (1993) 357}361.

[7] G. Debreu, The coeffcient of resource utilization, Econometrical 19 (1951)273}292.

[8] T. Koopmans, An analysis of production as an efficient combination of activities, in: T. Koopmans (Ed.), Activity Analysis of Production and Allocation, Wiley, New York, 1951.

[9] M. Farrell, The measurement of productive effciency, Journal of the Royal Statistical Society 120 (1957)253}281.

[10] A. Charnes, W. Cooper, E. Rhodes, Measuring the efficiency of decision making units, European Journal of Operational Research 2 (1978)429 }444.

[11]R.D.Banker, A.Charnes and W.W.Cooper, (1984), "Some models for estimating technical efficiency and scale efficiencies in data envelopment analysis", *Management Science*, Vol 30, no.9, pp 1078 – 1092.

[12]Coelli T, (1996). A guide to DEAP version 2.1. A Data Envelopment Analysis (Computer) Programs. CEPA working paper 96/98. University of New England Armidale.

[13]Lovell K.C.A. (1993); Production frontiers and Productive Efficiency, in Lovell et al (Eds),The measurement of Productive Efficiency, New York Oxford, Oxford University Press,pp. 3-67.

[14]Malmquist S. (1953). Index Number and indifference curve, Trabajos de Estadistica a pp-209-242.