Telecommunications Industry Efficiency: A Comparative Analysis of High and Middle Income Countries

Abstract

This study evaluates telecommunications industry efficiency in 19 countries grouped into high income countries (HICs) and middle income countries (MICs). Using data from 2001-2013 and a two-stage Data Envelopment Analysis (DEA), it finds that while HICs outperformed MICs, both of the groups exhibited improved technical efficiency, managerial effectiveness, and operational scale. Additionally, time in deregulation enhances technical and scale efficiency in HICs, however, the influence is insignificant in MICs. Labour productivity drives technical efficiency in HICs. Also, it augments managerial resourcefulness in HICs and MICs, however, its influence on scale efficiency is immaterial. Revenue per subscription enhance technical efficiency and managerial effectiveness in the two groups of countries. The relationship with scale efficiency, which is positive in HICs is irrelevant in MICs. Capital intensity has insignificant influence on managerial effectiveness in the two clusters of countries, however, it undermines technical efficiency in HICs and scale efficiency in MICs. Gross national income per capita is inconsequential to scale enhancement. However, it contributes to technical efficiency in the two categories of countries and managerial performance in HICs. Efficiency performances in HICs and MICs are insensitive to the industry's concentration level. Inflation has insignificant influence on scale efficiency in HICs and MICs. Also, it drives technical efficiency and managerial performance in MICs, but the influence in HICs is immaterial. The joint impact of labour productivity and capital intensity is irrelevant to operational scale in HICs and MICs, however, it is negatively associated with technical efficiency and managerial effectiveness in MICs. This empirical study provides additional insight that managers in the industry and policy makers will find useful during strategy formulation and policy deliberations.

Keywords: DEA, Efficiency, Telecommunications, Tobit.

1. Introduction

Technological innovation and deregulation continue to influence the telecommunications industry in many countries. On one hand, technological advancement has blurred the line between computers and telecommunications, creating competition from nontraditional platforms. On the other hand, regulatory reform in many countries have allowed the industry to rely more on market forces (Karamti & Kammoun, 2011; Li & Xu, 2004). Following deregulation in United Kingdom (UK) and United States (US) in the early 1980s, several developed and emerging economies have deregulated their telecommunications industries to promote competition and improve performance (Bortolotti, D'Souza, Fantini, & Megginson, 2002). Of particular interest is the efficiency of the industry, which studies have investigated in the context of input conversion into output. It is important to investigate the efficiency of the industry because the measure reflects on the success of deregulation. An increase in efficiency would signal better performance, benefiting customers in the form of improved services and lower prices (Usero & Asimakopoulos, 2013; Madden & Savage, 2001a). Cross-country studies (*e.g.,* Erber, 2005; Gokgoz & Demir, 2014; Torres & Bachiller, 2013) and single country studies (*e.g.,* Lee, Park, & Oh, 2000; Moreno, Lozano, & Gutierrez, 2013; Uri, 2006) focus largely on the industry and firm level efficiency and productivity in developed countries. The few studies on emerging countries with middle incomes are country specific (*e.g.,* Resende & Facanha, 2002; Sharma, Momaya & Manohar, 2010) or regional in focus (*e.g.,* Cabanda, Ariff & Viverita, 2004; Moshi, Mwakatumbula & Mitomo, 2013; Torres & Bachiller, 2013). Some studies (*e.g.,* Lee, Park, & Oh, 2000) report efficiency improvements, whereas others assert the contrary or indicate that efficiency varies with time (*e.g.,* Gokgoz & Demir, 2014; Petrovic, Bojkovic, & Stamenkovic, 2018; Uri, 2006). The incongruence in findings creates ambiguity that this research endeavors to resolve through a comparative analysis of the industry in designated high income countries (HICs) and middle income countries (MICs). The study explores periods from 2001-13 to provide insight on the industry's efficiency trends and performance over time. Emphasis on HICs and MICs is based on the notion that studies (*e.g.,* Torres & Bachiller, 2013; Madden & Savage, 2001a) highlight better performance from increased competition as rationale for deregulating the industry, however, the observation in Letza, Smallman, & Sun (2004) show that the desired improvements are not always attained. The comparison of HICs and MICs provides a better understanding of the similarities and differences in efficiency performance in the two groups of countries. In addition, it sheds light on variables that contribute to differences in performance, allowing the two categories of countries to learn from each other. As a result, managers in the industry and regulators are better able to identify periods of good and/or poor efficiency performance. Furthermore, by identifying the sources of efficiency and environmental factors with influence on it, this research provides insightful information on how to improve efficiency. Without this knowledge, managers in the industry and policy makers would lack empirical evidence needed to avoid counterproductive policy measures. The next section (Section 2) discusses related literature on efficiency performance of telecommunications industry. Section 3 describes the methodology and data. Discussion of the results and robustness checks are presented in Section 4. Section 5 provides the concluding summary and suggestions for future research.

2. Review of Literature

Efficiency entails using economic resources in ways that mitigate waste (Kumar & Gulati, 2008). Coelli *et al.* (2005) discuss efficiency from the perspective of technical efficiency (TE) and allocative efficiency (AE). Technical efficiency involves producing the maximum outputs from a given amount of inputs (Coeli *et al.,* 2005). Allocative efficiency, which occurs when inputs (*e.g.,* capital and labour) combination yields outputs at the lowest possible cost reflects the optimal mix of inputs given a particular price and technology constraint (Coeli *et al.,* 2005; Kumar, 2013; Uri, 2006). Evaluating efficiency and the influence of environmental factors are important to telecommunications industry managers and policy makers seeking improvement in performance. As such, a number of studies employ frontier and non-frontier methods to understand efficiency manifestations in the industry. Non-frontier econometric techniques in Wallsten (2001) study of the telecommunications industry in Africa and Latin America reveals that competition enhances efficiency. Using fixed effect model in the evaluation of the effect of privatization and competition on network expansion and efficiency, Ros (1999) suggests that privatization and competition improve efficiency. The frontier approach applied in Eber (2005) evaluation of the industry in US, UK, Germany, France, and Netherlands reveals that France and UK displayed better technical efficiencies. Although the study links efficiency difference among countries to time lag in adopting technology, it notes that the difference diminished with time. The frontier approach in Diskaya, Emir, & Orhan (2011) involves non-parametric data envelopment analysis (DEA). The analysis of firm level data from G8 countries and Turkey shows efficiency improvement. However, the sample size is small, and the study did not employ statistical analysis to determine if the efficiency of Turk Telecom differs from those of G8 countries. Petrovic, Bojkovic, & Stamenkovic (2018) examination of telecommunications industry in 22 countries in the domain of European Bank for Reconstruction and Development (EBRD) show efficiency improvement that vary with time. Nonetheless, the study finds that EU countries performed better than less wealthy South East European countries. Using DEA, Calabrese, Campsi, & Mancuso (2002) infer that efficiency gain is possible through input-output mix rather than through operational scale. The work of Torres & Bachiller (2013) involving a two-stage DEA unveils decline in technical and scale efficiency. Similarly, Gokgoz & Demir (2014) indicate technical and scale efficiency deterioration. Nonetheless, the finding that investment and competition affect efficiency is consistent with Fink, Mattoo, & Rahindran (2003). In addition, Hu & Chu (2008) show technical and scale inefficiency decline in the sample of firms investigated except KDDI of Japan and TNZ of New Zealand. In addition, the study indicates that telecommunications firms in affluent countries in Asia-Pacific displayed better efficiency than those in low-income and less developed areas. The study's analysis of environmental factors indicate that unlike GDP per capita, scope and scale economies that influence technical efficiency, the level of competition has no impact. Tsai, Chen, & Tzeng (2006) examination of leading global telecoms in different regions (*i.e.,* America, Asia-Pacific, and Europe) reveal that Asia-Pacific region displayed better efficiency than Europe and America, however the differences in performance are insignificant. Utilizing similar approach, Hung & Lu (2007) report that operational scale influence efficiency. However, the finding that Europe exhibits superior efficiency performance contrasts Tsai, Chen, & Tzeng (2006). In the case of Africa, Moshi, Mwakatumbula, & Mitomo (2013) show inefficiency in the industry. A study by Sharma, Momaya, & Manohar (2010) link technical inefficiency to managerial incompetence and improper operational scale. Unlike other studies, they assert that managerial underperformance contributes the most to inefficiency. Banker, Cao, Menon, & Natarajan (2010) show that growth in the industry in US is largely due to technological progress and providers with large operational scale and scope tend to perform better. Although limited to mobile telecommunications, these findings lend credence to the notion that operational scale improvement leads to better performance. In general, studies present mixed findings, pointing to efficiency improvement (*e.g.,* Diskaya, Emir, & Orhan, 2011; Mohamad, 2004) or deterioration (*e.g.,* Torres & Bachiller, 2013; Gokgoz & Demir, 2014). Some studies link efficiency outcomes to managerial competence in allocating inputs, however, there are studies that point to operational scale. Nonetheless, studies in the context of HICs and MICs comparison are lacking. This study aims to fill the gap in literature by providing an understanding of telecommunications industry efficiency and the influence of environmental factors in the two categories of countries. By identifying parallels between HICs and MICs and clarifying the differences between them, this study provides invaluable insights on what the two groups of countries could learn from each other, contributing to thoughtful policy decisions and the industry's viability.

3. Methodology and Data

3.1. The CRS and VRS DEA models

This research employs a two-stage Data Envelopment Analysis (DEA). The first stage uses DEA to assess the efficiency of the industry. The second stage utilizes Tobit model to evaluate the influence of environmental variables on efficiency. DEA can be input, or output oriented (Coelli *et. al.,* 2005; Yu et al., 2019). Input oriented DEA provides information on the magnitude of input reduction that would lead to efficiency increase, whereas the output oriented DEA identifies the output increase that is possible without simultaneous increase in input (Coelli *et. al.,* 2005). Similar to Torres & Bachiller (2013), this research adopts the input oriented DEA because managers in the industry have better control over inputs than they do over outputs. Assessing the technical efficiency of the industry under constant return to scale (CRS) is based on the assumption that each decision-making unit (DMU) is operating at optimum level (Charnes, Cooper, and Rhodes, 1978). In essence, with the CRS imposed, the presumption is that telecommunications industry in each country is operating at optimum scale, such that a change in inputs would result in proportional change in outputs (Uri, 2006). The general model as expressed in Charnes, Cooper, & Rhodes (1978, p. 430) and Cooper, Seiford, Tone, & Zhu (2007, p. 154) is:

$$Max\ h_0(\mu, v) = \sum_{r=1}^{s} \mu_r y_{r0} \ \ / \sum_{i=1}^{m} v_i x_{i0} \tag{1}$$

Subject to:

$$\sum\nolimits_{r=1}^{s} \mu_r y_{rj} \ / \sum\nolimits_{i=1}^{m} v_i x_{ij} \leq 1, \quad \text{j} = 1, \ldots\ldots,\text{n; Where: } \mu_r,\ v_i \geq 0 \tag{2}$$

Where n is the number of DMUs, s is the number of output, y_{rj} is the *r*th output data for *j*th DMU, m is the number of inputs, x_{ij} is the *i*th input data for the *j*th DMU. The weights of the variables are μ_r and v_i

Maximization results in:

$$\text{Max } Z_0 = \sum_{r=1}^{s} \mu_r y_{r0} \tag{3}$$

Subject to:

$$\sum\nolimits_{r=1}^{s} \mu_r y_{rj} - \sum\nolimits_{i=1}^{m} v_i x_{ij} \leq 0, \text{j} = 1, \ldots\ldots,\text{n; Where: } \mu_r;\ v_i \geq 0 \tag{4}$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \tag{5}$$

$0 < \varepsilon \leq \mu_r$ and $0 < \varepsilon \leq v_i$

The dual model is:

$$\text{Min } \theta_0 - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_i^+ \right) \tag{6}$$

Subject to:

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{i0} \qquad \text{where: } i = 1, 2, \ldots.., m \tag{7}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0} \qquad \text{where: } r = 1, 2, \ldots\ldots s \tag{8}$$

$$\lambda, s_i^-, s_r^+ \geq 0$$

The above CRS DEA model assesses efficiency without considering differences in operational scale of DMUs. However, market inadequacies may cause some DMUs to operate at suboptimal scale, resulting in biased CRS efficiency scores (Banker, Charnes, & Cooper, 1984; Hu & Chu, 2008). To remove scale bias, the VRS espoused by Banker, Charnes, & Cooper (BCC) (1984, p. 1085) and Banker, Cooper, Seiford, Thrall, & Zhu (2004, p. 346) was imposed. This model tolerates the possibility that a change in inputs may not result in proportional change in outputs. The BCC model is:

$$\text{Min } \theta_0 - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_i^+ \right) \tag{9}$$

Subject to:

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{i0} \qquad \text{where: } i = 1, 2, \ldots.., m \tag{10}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0} \qquad \text{where: } r = 1, 2, \ldots\ldots s \tag{11}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \text{ and } \lambda, s_i^-, s_r^+ \geq 0 \tag{12}$$

Where n is the number of DMUs (*e.g.,* telecommunications industries), x_{ij} is the *i*th input for the *j*th DMU, y_{rj} is the *r*th output for the *j*th DMU, m and s are the number of inputs and outputs, and s_i^- and s_r^+ are the input and output slacks. Based on the dual model, a DMU_0 of focus is technically efficient if $Min\ \theta_0 = \theta_0^* = 1$ and if there are no inputs and output slacks (Banker *et al.,* 2004). Similar to Naimy & Merheb (2014), this study utilizes three (3) inputs in the DEA model. The inputs include annual capital expenditures (CAPEX), yearly subscriptions (SUB), and employment (EMP). Unlike some studies (*e.g.,* Cho & Park, 2011; Moreno, Lozano, & Gutierrez, 2013) that espouse operators' view of performance with a single output (*e.g.,* revenue), this study embraces operators' and policy makers' views by incorporating two outputs (*i.e.,* revenues and teledensity) in the DEA model. Capital expenditures (CAPEX) and revenues, which are in U.S. dollars are inflation-adjusted with 2010 as the base year. The analysis involves thirteen years (*i.e.,* 2001-13) of data on 19 countries. The categorization of countries into HICs and MICs was based on gross national income per capita (GNI per capita), which is a measure used by The World Bank to classify countries into groups (The Word Bank, 2019). In addition, the approach has been used in Taskin & Zaim (1997). While the sample of countries investigated may differ in characteristics, each has deregulated telecommunications industry. The clustering into homogeneous groups (*i.e.,* HICs & MICs) reduces heterogeneity within each group (Dyson *et. al.,* 2001), making comparison of the two groups possible. The analysis, which covers a 13-year period reveals efficiency performance and trends over time. Furthermore, it provides ample information and insightful details about telecommunications industry efficiency in each of the two categories of countries. To identify the group with better performance, Mann-Whitney (Wilcoxon Rank-Sum) test was conducted at 95 percent confidence interval with HICs group as one (1) and MICs group as two (2). The null hypothesis (H_0) is that there is no statistically significant difference between the two categories of countries. The alternative hypothesis (H_a) is that there is statistically significant difference between the two groups of countries. The data sources for inputs, outputs, industry specific and macroeconomic variables include International Telecommunications Union (ITU), The World Bank, and OECD Communications outlook. Additional data sources include each country's national statistics agency, regulatory agencies, and empirical studies with focus similar to this research.

3.2. Tobit Model

The Tobit model used in the second stage of the analysis sheds light on the relationship between environmental variables and the first-stage DEA efficiency scores. While the variables in Kang (2010) are industry specific, other studies (*e.g.,* Torres & Bachiller, 2013; Gutierrez, 2003) combine industry specific and macroeconomic variables. The model in this study controls for industry specific and macroeconomics variables. The industry specific variables include NYRS to proxy the length of time the industry has been deregulated and the associated change in the industry (Moshi, Mwakatumbula & Mitomo, 2013; Li & Xu, 2004), subscriptions per employment (SubEmp) to denote labour productivity (Dabler, Parker, & Saal, 2002), and revenue per subscription (RevSub) to represent the financial soundness of the industry (Lee & Quayes, 2005). The other industry specific variables are capital expenditures per dollar of revenue (CapexRev), which is used to proxy capital intensity (Koi-Akrofi, 2013), and Herfindahl-Hirschman Index (HHI), which is the proxy for the concentration of the industry (Asimakopoulos & Whalley, 2017; Noam, 2005). The macroeconomic variables are gross national income per capita (GNIPC), which reflects income made by residents of a country (Fantom & Serajuddin, 2016), and consumer price index (CPI), which is the proxy for inflation in the economy (Byamaakhuu, Kwon, & Rho, 2014). The interaction term (*i.e.,* SubEmp*CapexRev) provides insight on the joint impact of labour productivity (SubEmp) and capital intensity (CapexRev). The model with industry specific and macroeconomic variables is:

$$E_{i\,t} = \beta_0 + \beta_1\, NYRS_{i\,t} + \beta_2\, SubEmp_{i\,t} + \beta_3\, RevSub_{i\,t} + \beta_4\, CapexRev_{i\,t} + \beta_5\, GNIPC_{i\,t} + \beta_6\, HHI_{i\,t} + \beta_7\, CPI_{i\,t} + \beta_8\, SubEmp_{i\,t} * CapexRev_{i\,t} + u_{i\,t}$$

where subscripts *i* and *t* denote countries and periods under study respectively. E_{it} indicates the efficiency of country *i* in period *t*, β_0 is the intercept, β_1 to β_8 are the coefficients of the variables. With efficiency scores as dependent variables, the analysis was carried out at 95 percent confidence level, specified left censoring limit of 0, and right censoring limit of 1. Parameters with positive signs are considered as having positive association with efficiency, and those with negative signs have negative relationship with efficiency. Coefficients with *p*-values of 0.05 or less have statistically significant connection with efficiency.

4. Results and Discussion

4.1. Efficiency Analysis

Table 1 shows the CRS technical efficiency (CRS TE) scores for the two categories of countries. The mean efficiency of 89 percent for HICs and 63.3 percent for MICs indicates that MICs is not as efficient as HICs. Nonetheless, the two groups of countries are technical inefficient as inputs could have been used to produce a higher level of outputs. Inputs in HICs could have produced an output level that is 1.1 times the current level, whereas inputs in MICs could have produced output level that is 1.6 times the current level. The finding that MICs is not as efficient as HICs is consistent with Petrovic, Bojkovic, & Stamenkovic (2018) observation that telecommunications industry in European Union (EU) are more efficient than those in less affluent South East European countries. Although the technical efficiency for MICs category is 71 percent of HICs, the CRS TE trends in Figure 1 show an increase from 2001 to 2013 in the two categories of countries, signifying technical efficiency improvement.

Better use of inputs in the industry in the two groups of countries may have contributed to the enhanced technical efficiency. During the period, the CRS TE gap between HICs and MICs shrank, revealing that MICs attained greater technical efficiency improvement. Additionally, HICs displayed an upward and relatively steady pattern, but MICs exhibited haphazard and widely varied pattern, which may have been due to later deregulation and adjustment to market mechanisms. In addition to assessing CRS TE, the pure technical efficiency (PTE), which provides an understanding of the effectiveness of managers in allocating inputs was evaluated by imposing VRS (Kumar & Gulati, 2008). The mean VRS TE score is 93.5 percent in HICs and 69.8 percent in MICs (Table 1), indicating that managers underperformed in the two categories of countries. The mean PTE in MICs is 75 percent of the level in HICs, suggesting that managers in MICs are less effective compared to their HICs counterparts. Nonetheless, the upward trends in VRS TE (Figure 2) show improvements in managerial effectiveness. Possibly, managers received training and gained experience that enabled them to better allocate resources (*e.g.,* employees and network infrastructures) and offer services (*e.g.,* mobile, data, etc.) to generate more subscriptions and higher revenue.

The nature of inefficiency was delineated using classifications in Norman & Stoker (1991). The mean CRS TE and VRS TE scores suggest that the HICs category is marginally inefficient (CRS TE < 1; 0.9 < VRS TE < 1), thus, slightly decreasing inputs or increasing outputs will improve performance. On the other hand, the MICs group is distinctly inefficient (CRS TE < 1; VRS TE < 0.9), indicating difficulty in attaining efficiency in the short run by altering inputs mix (Demirbag, Tatoglu, Glaister, & Zaim, 2010). In the HICs category, three countries (*i.e.,* Belgium, New Zealand, and US) are robustly efficient (CRS TE = 1; VRS TE = 1), whereas two (*i.e.,* Chile and Canada) are distinctly inefficient (CRS TE < 1; VRS TE < 0.9). In addition, one (*i.e.,* Germany) is marginally efficient (CRS TE < 1; VRS TE = 1) and the remaining four (*i.e.,* Australia, Japan, South Korea, and UK) are marginally inefficient (CRS TE < 1; 0.9 < VRS TE < 1). In the MICs group, all but Kenya show distinctly inefficient status. Additionally, the scale efficiency of the industry was assessed. The results in Table 1 show mean scale efficiency score of 95 percent for HICs and 91.5 percent for MICs, suggesting that the two clusters of countries operated at suboptimal scale. Although MICs displayed a more precarious scale inefficiency, trends in Figure 3 reveal a level of improvement better than the HICs group. Furthermore, the observed scale inefficiency occurred when the industry was technically inefficient, affirming Sung (2012) and Naimy & Merheb (2014) findings of relationship between operational scale and efficiency. The Mann-Whitney (Wilcoxon Rank-Sum) test used to ascertain the statistical significance of the difference in technical efficiency, PTE, and scale efficiency performance in the two categories of countries reveal z values of 9.03, 8.95, and 4.90 for the CRS TE, VRS TE, and scale efficiency respectively. These z values are statistically significant at 5 percent, indicating that the high efficiency scores for the HICs category are significantly different from MICs, which implies that the HICs group performed better than the MICs group.

Table 1: Mean Estimate of Efficiency scores

High Income Countries (HICs)					**Middle Income Countries (MICs)**			
	CRS TE (%)	**VRS TE (%)**	**SE (%)**			**CRS TE (%)**	**VRS TE (%)**	**SE (%)**
Australia	90.3	94.6	95.3		Brazil	81.6	86.3	94.7
Belgium	100	100	100		China	47.9	52.1	92.0
Canada	79.6	80.2	99.2		India	46.5	47.6	97.6
Chile	58.6	66.5	88.3		Indonesia	57.9	61.0	94.8
Germany	98.5	100	98.5		Kenya	65.4	92.9	68.0
Japan	94.5	97.3	97.1		Mexico	73.7	75.9	96.9
New Zealand	100	100	100		Nigeria	50.6	61.6	85.2
South Korea	89.5	96.4	92.8		South Africa	66.5	69.2	95.9
United Kingdom	78.4	99.6	78.9		Turkey	79.7	81.1	98.3
United States	100	100	100					
Mean	**89.0**	**93.5**	**95.0**		**Mean**	**63.3**	**69.8**	**91.5**
Median	**92.4**	**98.4**	**97.8**		**Median**	**65.4**	**69.2**	**94.8**
Standard Deviation	**13.4**	**11.2**	**6.8**		**Standard Deviation**	**13.4**	**15.5**	**9.7**

Note: CRS TE: Constant return to scale technical efficiency, VRS TE: Variable return to scale technical efficiency, SE: Scale efficiency

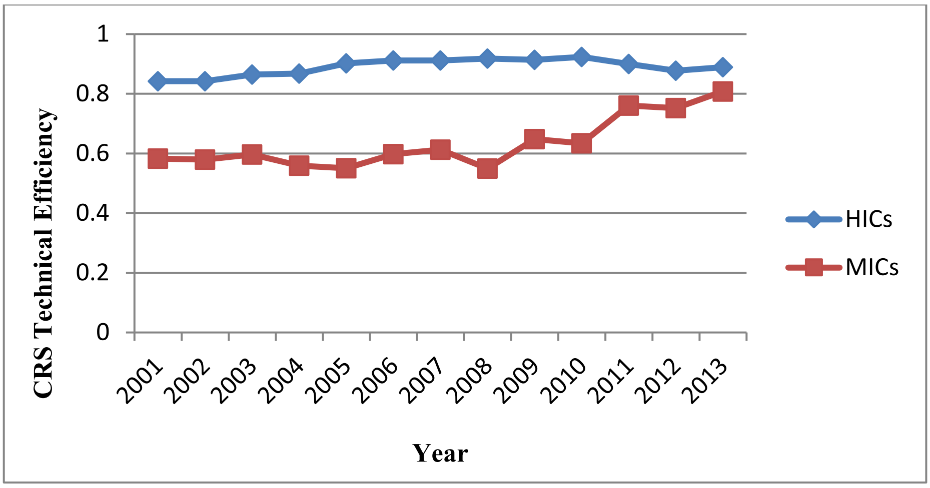

Figure 1: CRS TE Trends

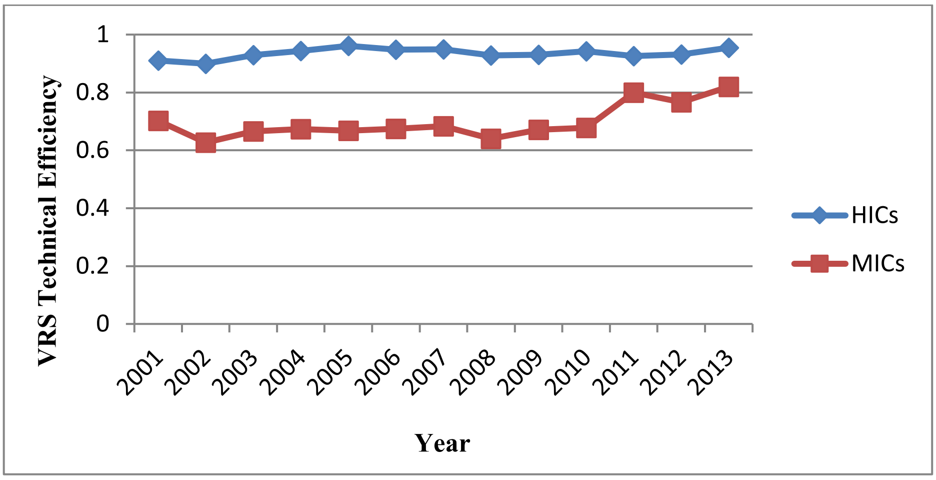

Figure 2: VRS TE Trends

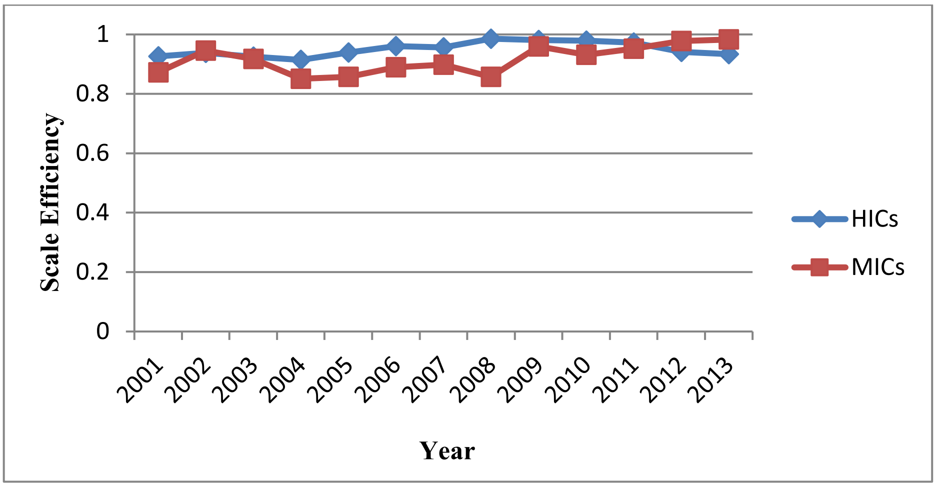

Figure 3: SE Trends

4.2. Determinants of Efficiency

It should be noted that in the second stage regression, the endogeneity problem can be associated with some of the environmental variables. Endogeneity may occur due to omitting a variable that should have been in the model, correlation between an explanatory variable and the error term, simultaneity, and reverse causality between dependent variable and an independent variable (Antonakis, Bendahan, Jacquart, & Lalive, 2014; Bascle, 2008; Zhang, 2005; Zhang et al., 2017). While it is possible to mitigate endogeneity, complete prevention can be difficult to achieve (Bun & Harrison, 2019). GNIPC and HHI are potentially endogenous. Using lagged values is one approach to mitigate this problem, which has been used in this study. The results are largely consistent with those without using lags. However, using lags results in a reduction in observations, which is undesirable for this study as our sample is relatively small. Therefore, we only report the results without using the lagged values.

Table 2 is the Tobit model outputs for all of the countries combined, HICs, and MICs. NYRS has a significant negative association with CRS TE. The grouping of countries into HICs and MICs reveals that the negative influence in not statistically significant in MICs, indicating that time progression constrains technical efficiency in HICs, but the effect on technical efficiency is MICs is not pertinent. The link between NYRS and VRS TE is negative but statistically insignificant in the model for all of the countries combined and the two clusters of countries, suggesting that managerial resourcefulness is unhindered by time progression. Although insignificant, the observation of a negative association could indicate that managerial incompetence is possible regardless of the length of time in deregulated condition. It could be that innovations in the industry require managers to update their knowledge and skills to be effective. In addition, NYRS shows insignificant positive effect on scale efficiency in MICs, however, the influence on scale efficiency in HICs is negative and statistically significant. The insignificant link between length of time in deregulation and scale efficiency in MICs suggests that the length of time in deregulation has no considerable influence on scale efficiency in MICs. In contrast, the significant negative association with scale efficiency in HICs highlights the hampering effect of time progression on scale efficiency. This could be the consequence of high level of saturation in HICs, which is hindering subscriptions and revenue growth. Additionally, given continuous innovation in the industry, the significant negative relationship with scale efficiency could reflect the inability to adjust operational scale quickly to the most productive size. Labour productivity (SubEmp) has significant positive association with CRS TE and VRS TE when HICs and MICs are integrated (Table 2). The categorization of countries into HICs and MICs reveal positive relationship with CRS TE and VRS TE, however, the link with CRS TE in MICs is insignificant. Furthermore, the relationship between labour productivity and scale efficiency is positive and statistically insignificant. The observation relating to the grouping of countries into HICs and MICs also reveal statistically insignificant relationship, however, unlike in HICs where the sign of the coefficient is positive, in MICs, it is negative. These findings suggest that high labour productivity contribute to technical efficiency in the two groups of countries, however, it drives managerial effectiveness in HICs. Nonetheless, the influence is inconsequential to operational scale efficiency in the two groups of countries. The observed positive association with technical efficiency could be due to investment in technology and automated systems, which allow the industry to be productive by maintaining employment growth at a lower rate than subscriptions growth. The finding that labour productivity is irrelevant to scale is startling. Plausibly, with increase in labour productivity, firms in the industry delay operational scale adjustment. Revenue per subscription (RevSub) has statistically significant positive relationship with CRS TE and VRS TE in the two clusters of countries, indicating that high revenue per subscription contributes to technical efficiency and the resourcefulness of managers in allocating inputs in the two groups of countries. Furthermore, while revenue per subscription shows insignificant positive relationship with operational scale when the group of countries were integrated, the association with operational scale is positive and significant in HICs, but insignificant in MICs. This finding indicates that unlike HICs, MICs as a group are indifferent to altering operational scale based on revenue per subscription considerations.

Capital intensity (CapexRev) has a statistically insignificant connection with VRS TE, however, the sign of the coefficient is negative in HICs, whereas it is positive in MICs. Additionally, without clustering countries into HICs and MICs, capital intensity exhibits insignificant negative association with CRS TE. With the segmentation of countries into HICs and MICs, the observed relationship between capital intensity and CRS TE is negative. However, unlike in MICs where the negative association is insignificant, in HICs, it is statistically significant, suggesting that capital intensity undermines technical efficiency in HICs. Although capital intensity is not relevant to CRS TE in MICs, the significant negative link in HICs could be due to the disincentive to invest in network infrastructure if return on investment is inadequate. Furthermore, capital intensity has a statistically significant negative correlation with scale efficiency when the countries were ungrouped. Separating countries into HICs and MICs produced a relationship that is negative and statistically significant in MICs.

Although the link between capital intensity and scale efficiency in HICs is unimportant, the finding that it is statistically significant in MICs suggests that high capital expenditure per dollar of revenue has unfavourable influence on scale efficiency in MICs. This finding indicates that enhanced operational scale efficiency is possible in MICs, but firms in the industry would have to reduce capital expenditure per dollar of revenue by collaborating on the construction and/or use of telecommunications infrastructure. Without isolating countries into HICs and MICs, Gross national income per capita (GNIPC) exhibits significant positive connection with CRS TE and VRS TE. Also, when countries were separated into HICs and MICs, the association with CRS TE is positive and statistically significant, indicating that technical efficiency in HICs and MICs tend to increase with GNIPC. The relationship with VRS TE is positive and significant in HICs, whereas it is positive and insignificant in MICs. This finding suggests that high GNIPC promote managerial effectiveness in HICs, however, it is inconsequential to the effectiveness of managers in MICs. The link between GNIPC and scale efficiency is statistically insignificant when countries in the study were integrated and for the two groups of countries, demonstrating that GNIPC has no discernable influence on operational scale efficiency in the two categories of countries. Although GNIPC is a glimpse of wellbeing of a country's population, it may not reflect actual income distribution among the population (Fantom & Serajuddin, 2016). In view of this, high GNIPC may not automatically indicate more spending on telecommunications products and services, making it unimportant to operational scale efficiency. Industry concentration (HHI) is indicative of the structure of the industry and the level of competition (Noam, 2005). It has statistically insignificant connections with the CRS TE, VRS TE, and scale efficiency in the two categories of countries, indicating that HHI is irrelevant to measures of efficiency performance in the two groups of countries. While this finding deviates from Moreno, Lozano, & Gutierrez (2013), it augments Hu & Chu (2008) and Torres & Bachiller (2013) in refuting the notion that more competition improves efficiency. The unimportant influence on efficiency is probable in that licensing requirements and firm imposed barriers (*e.g.,* economies of scale and network access control) limit competition, making it less of a consideration (Torres & Bachiller, 2013).

Consumer price index (CPI) has statistically significant positive link with CRS TE in the combined group of countries. Sequestering reveals an insignificant positive relationship in HICs but significant positive connection in MICs, showing that CPI contributes to technical efficiency in MICs. The benefits to technical efficiency in MICs could be due to the ability of firms in the industry to increase/decrease tariffs at a rate higher/lower than the level of inflation/deflation in the economy. Also, unlike in HICs where CPI exhibits an insignificant negative connection with VRS TE, the significant positive correlation with VRS TE in MICs indicates that inflation induces managerial resourcefulness in the MICs. The relationship between CPI and scale efficiency is positive and statistically significant for the combined group, however, the isolation into HICs and MICs shows insignificant relationship. The finding of insignificant positive correlation between the level of inflation and operational scale in HICs and MICs signifies that inflation could drive operational scale, however, it has no meaningful influence in the two categories of countries. The interaction term (SubEmp*CapexRev) has insignificant connection with CRS TE, VRS TE, and scale efficiency performance in HICs. Although it has a negative and significant relationship with CRS TE and VRS TE in MICs, the influence on scale is insignificant. While labour productivity from capital investments could be realized by hiring and/or training employees after introducing new infrastructures and technologies (Samoilenko & Ilienko, 2015), the gain in labour productivity may not sufficiently counteract the impact of capital intensity. This could happen if training is inadequate and/or if employment levels are not commensurate with capital spending on infrastructures, stifling managerial performance and technical efficiency.

Table 2: Tobit model outputs									
	All countries (n = 19)			**HICs (n = 10)**			**MICs (n = 9)**		
	CRS TE	**VRS TE**	**SE**	**CRS TE**	**VRS TE**	**SE**	**CRS TE**	**VRS TE**	**SE**
NYRS	-0.009693*	-0.006227	-0.005920*	-0.013381*	-0.005731	-0.010618*	-0.010501	-0.012410	0.002256
SubEmp	0.000416*	0.000484*	0.000066	0.000550*	0.001074*	0.000134	0.000154	0.000276*	-0.000058
RevSub	0.000367*	0.000338*	0.000115	0.000461*	0.000324*	0.000294*	0.000422*	0.000477*	0.000049
CapexRev	-0.047759	0.194122	-0.143221*	-1.42802*	-0.298092	-1.142649	-0.035252	0.178702	-0.13281*
GNIPC	4.16e-06*	5.62e-06*	1.14e-06	7.74e-06*	0.000011*	2.81e-06	0.000023*	0.000017	8.43e-06
HHI	4.04e-06	7.72e-06	-3.46e-06	4.67e-06	0.00001	-0.000014	-0.000014	-0.000012	-5.57e-06
CPI	0.005212*	0.003307*	0.002811*	0.003226	-0.002934	0.003351	0.006542*	0.006010*	0.001438
SubEmp*CapexRev	-0.001295*	-0.001799*	-0.000049	0.001955	-0.000042	0.001939	-0.001028*	-0.001651*	0.000249
Log Likelihood	18.36	-35.63	74.37	25.33	-7.08	26.72	28.08	-5.41	67.43
Number of Obs.	247	247	247	130	130	130	117	117	117
LR Chi2(8)	234.12	175.95	92.29	137.75	83.02	65.35	69.68	46.02	46.53
Prob > Chi2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pseudo R2	1.19	0.71	-1.63	1.58	0.85	5.48	5.15	0.81	-0.53

*p<0.05

5. Conclusion

This research comparatively examines efficiency performance of telecommunications industry in HICs and MICs between 2001 and 2013. It provides an understanding of the industry in in the two groups of countries. Findings from the first stage of the two-stage DEA show that technical inefficiency, managerial ineffectiveness, and inappropriate scale exist in the two categories of countries. Although the HICs group performed better than MICs on measures of efficiency performance, improvements in MICs suggests that it is catching up to HICs, which is consistent with previous research such as Madden and Savage (2001b). The findings also show that managerial underperformance and unsuitable operational scale triggers technical inefficiencies in the two groups of countries, the technical inefficiency is mostly the result of managerial ineffectiveness. In view of this, prior to focusing on operational scale adjustments, the industry in the two categories of countries would need to enhance the capabilities of managers in allocating resources. In the short run, efforts at addressing the marginal inefficiency in HICs could involve training and incentives for managers to optimize resource mix and allocation. The lingering inefficiency in MICs would require long run focus on moving the industry to the most productive operational scale, and improving the utilization of resources through streamlined operations and automated service delivery.

Findings relating to the determinants of efficiency that show time progression undermine technical and scale efficiency in HICs could be due to the inability of the industry in HICs to adjust operational scale. Given new technology and saturation of the industry in HICs, the undermining effect of time progression on technical efficiency highlights the need for HICs to adapt operational scale. In addition, the insignificant negative link between time progression and VRS TE in HICs and MICs show that it is unimportant to managerial resourcefulness, however, the negative relationship should be a concern for the industry. To avoid undermining managerial capability in allocating resources, managers in the industry may have to upgrade their skills, and demonstrate versatility in responding to technological change and new demands from customers (Asimakopoulos & Whalley, 2017). The finding that labour productivity is insignificantly associated with scale efficiency indicates that firms in the industry in the two groups of countries see no incentive to adjust operational scale when labour productivity is high. Additionally, the finding that labour productivity drives technical efficiency suggests that enhanced technical efficiency could be achieved by improving labour productivity, but it is irrelevant in MICs. Furthermore, the positive correlation between labour productivity and effectiveness of managers in the two groups of countries is significant, showing that to enhance managerial effectiveness, it is incumbent on managers in the industry to seek labour productivity improvement, which may be achieved through employee training, skills development, and better management. The finding that revenue per subscription boosts scale efficiency in HICs but not in MICs reflects MICs approach to operational scale adjustment. Additionally, seeing that revenue per subscription drive technical efficiency and resourcefulness of managers in the two categories of countries, the industry would benefit from a strategy involving revenue growth through price adjustment and/or offering more product options and services to customers. Capital intensity is negatively correlated with CRS TE, however, the significant negative link in HICs reveals that it undermines technical efficiency in HICs. Additionally, the finding that it has irrelevant influence on technical efficiency in MICs but detracts from the operational scale could signal that MICs as a group has accumulated unnecessary capital expenditures. Sharing facilities and collaborating on infrastructure construction would curtail capital expenditures per dollar of revenue in MICs, leading to better operational scale. GNIPC has no meaningful influence on scale efficiency in the two categories of countries. It exhibits positive and significant relationship with technical efficiency in the two groups of countries, suggesting that regardless of country classification, increasing GNIPC results in better technical efficiency. The influence on effectiveness of managers in the two groups of countries differ. In HICs, the significant positive correlation with managerial effectiveness indicates that high GNIPC stimulates the effectiveness of managers. In MICs, the insignificant positive link shows that the effect is immaterial. The concentration of the industry is inconsequential to technical efficiency, managerial effectiveness, and operational scale regardless of whether the industry is in HICs or MICs category. The broad finding that inflation correlates positively with technical efficiency suggests that general increase in price enhances technical efficiency. In MICs, the beneficial influence on technical efficiency may stem from the ability of firms in the industry to increase/decrease prices at a rate higher/lower than inflation/deflation in the economy. Furthermore, unlike in MICs where inflation also contributes to managerial resourcefulness, it has an insignificant negative effect on managerial effectiveness in HICs. It could be that high rate of inflation impedes managerial ability in securing adequate resource, constraining effectiveness of managers in the industry, nonetheless, the effect it is insignificant. Also, countries in the MICs group may have experienced high rate of inflation and price volatility that reduce the purchasing power of money (Mustapha & Khalid, 2013). The difficulty in predicting inflation may compel managers in the industry in MICs to be resourceful in using inputs. Thus, it is important to promote policies that help managers in the industry understand the threats associated with inflation, and to develop the requisite expertise in taking actions that will mitigate the risk of inflation. Furthermore, inflation has no meaningful effects on scale efficiency in the two groups of countries, suggesting that managers in the industry may have anticipated the probable level inflation and/or may have made accommodation for inflation when making operational scale decisions. The joint impacts of labour productivity and capital intensity impair technical efficiency and managerial effectiveness in MICs. In view of this, adjustments to hiring and employee training and development are essential after introducing new telecommunications technology and infrastructures. Unlike the approach in other studies (*e.g.,* Diskaya, Emir, & Orhan, 2011; Demirbag *et. al.,* 2010; Tsai, Chen, & Tzeng, 2006) that did not regress the DEA efficiency scores against environmental variables, the methodology in this study involves regressing efficiency scores against a combination of industry specific and macroeconomic variables. This approach provides a better understanding of efficiency performance and related environmental variables. Although the variables associated with efficiency shed light on the determinants of efficiency, this study does not advocate that these variables have causative effects. Nonetheless, the findings provide information on how to improve efficiency so that managers in the industry and policy makers can avoid actions that undermine efficiency. Categorizing the countries into HICs and MICs made it possible to make inferences relating to the two categories of countries, however, care should be exercised when generalizing the findings in this study. To increase the prospect for generalization of the findings to a wider array of countries, future research should apply mixed research method and/or use a larger sample of countries. DEA is suitable in that it allows the use of multiple inputs and outputs without any assumption about the functional form of the model, nonetheless, it is necessary to note that DEA does not have the ability to perform statistical tests or deal with measurement error (Coelli *et al.,* 2005). Future research should consider using parametric Stochastic Frontier Analysis (SFA) that accommodates statistical tests, however, it requires that the functional form of the production function be specified (Coelli *et al.,* 2005). The results should be compared to DEA findings to determine if the two methodologies produce outcomes that are comparable. In addition, future research should investigate the allocative and cost efficiency of the industry, which will provide information on reduction in costs should the industry attain efficiency status.

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