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Empirical Analysis of Performance Evaluation of Telecom Companies in Republic of Congo Based on DEA Model

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Abstract: This study evaluated price innovation impact on the telecommunication industry using a nonparametric approach based on linear programming which is conducted to measure the relative efficiency of a set of similar Decision-Making Units (DMUs). The DEA model evaluated the efficiency of various prices for the different kinds of services. Each company was assigned a set of efficiency scores for the period 2009 to 2016. Thus the data for this study was collected through an individual's company website and by visiting the company for the periods 2009-2016. The sample comprises four telecommunication companies in Congo. The analysis measured DEA and FDH technical efficiency scores using the Efficiency Measurement System (EMS Version 1.3, 2000). Therefore the results showed two out of seven variables are found statistically significant at the significant level of 0.05. The negative coefficient of large indicates that a large firm is more likely efficient than a small firm. The results also show that government ownership-based firm is more likely to be efficient than the domestic ownership-based firm.

Keywords: Performance Evaluation, Congo Telecom Industry, Tobit Model, DEA (Data Envelopment Analysis)

Introduction

Innovation has become a key force for all enterprises to achieve sustainable development. As a hot field at this stage, the telecommunications industry has made important contributions to promoting the development of the world economy through science and technology. As an important core of the company's development strategy. Traditional innovations are multidirectional technology and management innovations. Enterprises aim to improve their core competitiveness by providing better product quality and service. The global telecommunications industry is developing rapidly. The telecom companies in the Republic of the Congo have not shown obvious differences in their pursuit of technological innovation and management innovation. If the focus is shifted to the price innovation of products and services, it will bring sustainable development to enterprises. Continuous source of power and enhance the market competitiveness of enterprises. The telecommunications industry in the Republic of the Congo has completed the transition from monopoly to free competition, and the complete competitive market provides conditions for the development of telecommunications companies of different sizes. Price innovation is related to the survival and development of telecom companies in the market competition. It is transmitted to end users in the direct way of price information.

The key technical approach used in this study is a nonparametric approach based on linear programming to assess the impact of price innovation on the performance of the telecommunications industry. The data for the four telecommunications companies MTN, AIRTEL, WARID and AZUR in Brazzaville, Republic of Congo, 2009-2016 are The research sample, with price innovation as the entry point, carried out a comprehensive performance analysis of the four telecommunications companies in Brazzaville, Republic of Congo, and further analyzed the factors affecting the performance. The main contents include:

(1) Analysis of performance evaluation elements. Based on the analysis of the development of the telecommunications industry in the Republic of the Congo, identify the key factors affecting the performance of the telecommunications industry. The input factors include telephone call elements and SMS elements, and the output elements mainly include business volume elements.
(2) Construct a performance evaluation index system. After in-depth analysis of the key factors affecting the performance of the telecommunications industry, the representative indicators are selected by principal component analysis, including input telephone charges, outgoing telephone charges, international telephone charges, sending SMS fees, receiving SMS fees and international SMS fees and

output indicators include user volume and revenue to build a performance evaluation indicator system for the telecom industry in the Republic of the Congo.

(3) Construct a performance evaluation model and perform performance analysis on the research sample. The DEA model, the variable-weight DEA model based on output, the two stage DEA model and the FDH model are used to evaluate and analyze the performance of telecom companies in Brazzaville, Congo, respectively. The Tobit model is further constructed to show the relationship between variables, to identify the key factors affecting the performance of telecom enterprises, and finally to provide targeted recommendations for telecom enterprises to improve their business performance.

The innovations of this paper mainly include: (1) According to the characteristics of the telecom industry in the Republic of the Congo, design the performance evaluation indicators of telecom enterprises from three dimensions: telephone call elements, short message elements and business elements; (2)A comprehensive evaluation method combining principal component analysis with DEA and FDH to comprehensively analyze the performance of the telecom industry in the Republic of the Congo; (3) to analyze the factors affecting the efficiency of the enterprise through Tobit analysis on the basis of performance evaluation, to enhance the telecommunications industry Provide guidance on performance.

1. Data Collection and Empirical Analysis

In this empirical analysis we are aiming to show how the price innovation impacts the telecommunication companies in the republic of Congo. First and foremost we would discuss in detail about the methodology used to undertake this empirical analysis. Then we will introduce the factors of innovations and the performance indicators used to study the impact of innovations on the telecommunication companies' sales. The statistical analysis is done in two main parts: The qualitative analysis and the quantitative analysis. In the qualitative analysis, we use the Excel spreadsheet to generate the graphic of the mobile phone subscribers, the total income of calls and SMS, and then we combine them with the graphics of the dependent variables that the unit price of outgoing calls and SMS, to analyze the trend of the curves and draw some concluding remarks. After the qualitative analysis we then move to the quantitative analysis with the DEA model. We end up the chapter with Tobit Regression analysis. Our statistical analysis follows the framework:

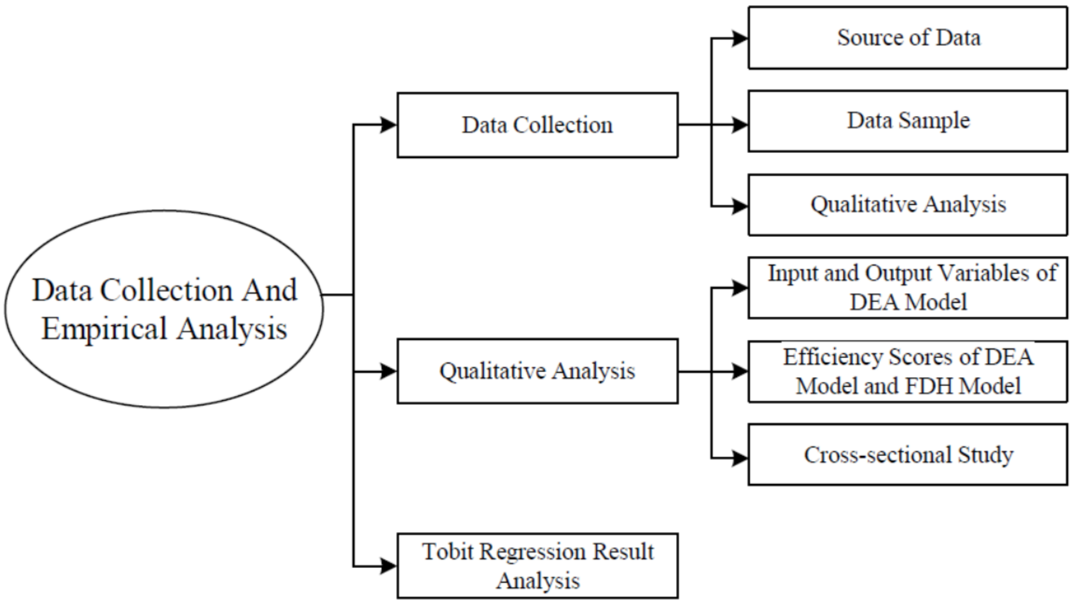

Figure 1 Research Analysis Framework

1.1 Data Collection

1.1.1 Source of Data

The data used in this research are mainly secondary data. Secondary data are the data collected by a party not related to the research study but collected these data for some other purpose and at different time in the past. If the researcher uses these data then these become secondary data for the current users. These may be available in written, typed or in electronic forms. A variety of secondary information sources is available to the researcher gathering data on an industry, potential product applications and the market place. Secondary data is also used to gain initial insight into the research problem. Secondary data is classified in terms of its source – either internal or external. Internal, or in-house data, is secondary information acquired within the organization where research is being carried out. External secondary data is obtained from outside sources. There are various advantages and disadvantages of using secondary data (shodhganga, 2012). In this research all our data were taken directly from the report of the regulatory telecommunication organization of Congo.

1.1.2 Data Sample

Sampling frame is a list or other record of the population from which all the sampling units are drawn (Collis and Hussey, 2003:155). In this study, a number of sampling frames were consulted in order to determine which one or what combination would be suitable for the study. In our target population we are doing our analysis within the period going from 2009 to 2016 (i.e. 8 years of observations) and 32 DMUs that we will observe during that time frame. The sample company name and identification is shown in Table -1.

Table - 1 The Data of Sample

DMU Name	outc (Input)	inc (Input)	outci (Input)	outsms (Input)	insms (Input)	outsmsi (Input)	Subscribers (Output)	Income (Output)
AIRTEL2009	95	79	99	21	22	82	1274	90164
AIRTEL2010	74	51	63	9	58	124	1666	109479
AIRTEL2011	50	88	88	19	20	126	1672	110321
AIRTEL2012	96	51	85	22	45	117	2548	90164
AIRTEL2013	70	89	59	8	55	119	3332	218958
AIRTEL2014	55	52	73	19	43	107	1672	110321
AIRTEL2015	73	54	86	21	54	125	2548	270492
AIRTEL2016	72	60	69	22	49	117	6664	656874
WARID2009	97	96	82	20	24	121	3344	110321
WARID2010	69	69	69	15	18	106	5096	540984
WARID2011	97	54	92	7	52	78	13328	1970622
WARID2012	51	80	93	20	24	86	3344	330963
WARID2013	66	51	55	24	49	106	10192	1081968
WARID2014	74	94	79	11	43	84	13328	3941244
WARID2015	78	65	71	23	44	108	6688	330963
WARID2016	67	79	80	19	30	100	10192	1081968
AZUR2009	56	74	87	14	34	112	13328	11823732
AZUR2010	85	90	75	25	42	78	13376	992889
AZUR2011	70	95	90	21	46	109	10192	1081968
AZUR2012	79	80	97	8	31	80	13328	11823732
AZUR2013	73	84	52	20	57	122	26752	992889

AZUR2014	81	92	98	16	35	122	10192	1081968
AZUR2015	69	99	51	10	64	105	26656	35471196
AZUR2016	50	100	99	8	34	102	53504	992889

The data for this study are collected through individual's company website and by visiting the company for the periods 2009-2016. The sample is comprising four telecommunication company in Congo.

The previous literature suggests that DEA researchers concentrate on the homogeneity assumption of the DMUs than the definite number of DMUs. Homogeneity in DMUs implies that DMUs have comparable inputs and outputs, parallel objectives and providing similar services. Cooper et al. suggested policy for the selection of a sample such as $n \geq max\{m \times s, 3(m + s)\}$. It means that the number of observations (n) should be greater than or equal to the maximum of the products of inputs (m) and outputs (s) and three times the sum of the number of inputs and outputs. The sample size of this study also matched the criteria explained above. The number of observation of this research is $n = 32$ (See Error! Reference source not found.), which is greater than max {12, 24} while m = 6 and$s$ = 2. The large sample size increases the reliability of DEA scores (Radhakrishnan, 2014). The DMUs numbered from 1 to 8 exhibits the MTN company, DMUs from 9 to 16 represents AIRTEL company, from 17 to 24 signifies WARID and 25 through 32 represents AZUR for the year 2009 to 2016. Table- 2 shows the sample of telecommunication company with six inputs and two outputs.

Table- 2 The Sample of DEA Setup

DMU No.	DMU Name	outc (Input)	inc (Input)	outci (Input)	outsms (Input)	insms (Input)	outsmsi (Input)	Subscribers (Output)	Income (Output)
1	MTN2009	76	154	120	20	39	118	1274	90164
2	MTN2010	45	89	89	7	23	75	1666	109479
3	MTN2011	49	69	76	5	40	79	1672	110321
4	MTN2012	89	50	90	21	57	108	2548	270492
5	MTN2013	87	73	98	22	27	115	3332	328437
6	MTN2014	52	55	75	10	53	103	1672	330963
7	MTN2015	55	67	91	9	27	82	2548	270492
8	MTN2016	88	70	64	8	65	111	3332	356874

The output-oriented linear programming setup for MTN company is formulated as follows under CRS assumption:

2. Empirical Analysis of Performance Evaluation

This section will describe the dataset used in this study for the various analysis and findings of the different types of analysis. As we described in chapter 6, the formulation of a linear program for each firm in the sample for employing DEA model. This study focuses on an output-oriented model for both CRS and VRS specifications. For the period 2009-2016, cross-sectional and time series analysis are employed. After then FDH efficiency score is estimated for a comparative study.

The DEA scores obtained from the first stage will be employed in the second stage to bootstrapped using Simar, L., & Wilson, P. W. (2000) to solve for probable bias associated with the efficiency estimation procedure. Due to the serial correlation between the estimate efficiency scores of the firm, there might have bias associated with the DEA estimation procedure. This bias will be solved using the bootstrap algorithm.

In the third stage, a Tobit model is used to regress the factors affecting firm efficiency. Power outage, firm size, ownership type and the generation of the network are part of those variables.

2.1 Input and Output Variables of DEA Model

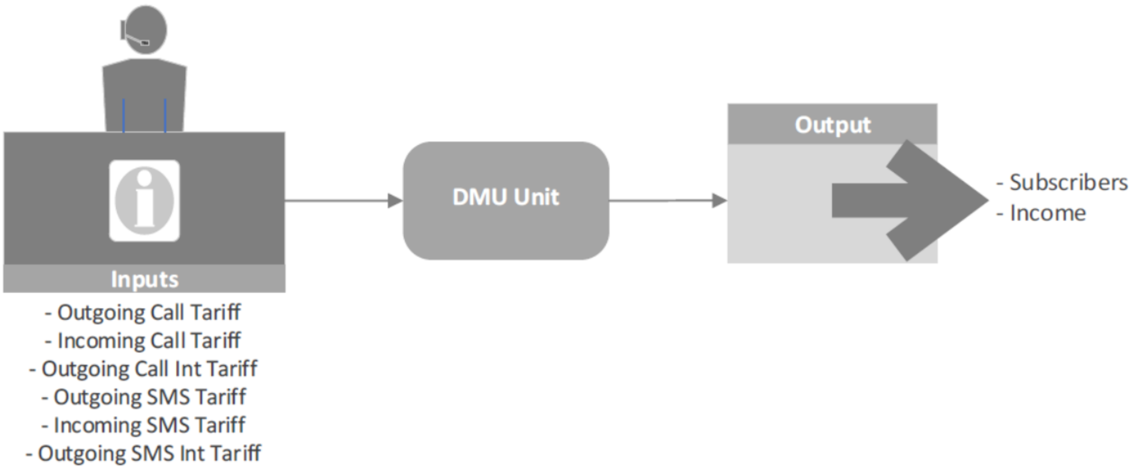

Figure 2 Service Production Process of telecommunication Industry

As stated in the research framework we use two main products to illustrate the impact of the innovation in the performance of telecommunication companies in the Republic of Congo. These two products are: the phone calls and the SMS. For both products we will have the outgoing and incoming local and international calls and SMS as our main independent variables. The innovation here can be seen on the price offered to the clients. So we have a price innovation 1 and a price innovation 2, respectively for the calls and SMS. Our statistical or empirical analysis consist of studying the impact of these two innovations on the performances of the telecommunication companies. To measure the performances of the telecommunication companies we have used two variables: the Sales and the Clients or Subscribers (Figure 10).

Farrell's (1957) measured DEA and FDH technical efficiency scores using the Efficiency Measurement System (EMS Version 1.3, 2000) which is designed by Holger School and FEAR 1.0 (Wilson, 2008) using statistical package R.EMS is appropriate measurement process to handle multiple inputs and outputs for various types of model orientations such as input/output/non and production technologies e.g. constant returns to scale/ variable returns to scale.

The bootstrapped DEA scores also examined for the two-stage DEA using FEAR 1.0 (Wilson, 2008). This study conducted cross-sectional and time series analyses for the period 2009-2016. This study examined efficiency scores through output-oriented model by employing both CRS and VRS models. On the other hand, both DEA and FDH efficiency scores are estimated for a comparative study.

Table 3 Summary Statistics of Input and Output Variables

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Input Variables					
outc_i	32	54.8125	30.10888	7	169
inc_i	32	82.59375	31.59406	40	180
outcint_i	32	112.0938	35.52587	62	195
outsms_i	32	14.8125	13.42707	1	51
insms_i	32	32	7.504837	20	50
outsmsi_i	32	68.78125	30.59173	17	126
Output Variables					
subscriber_o	32	1089.156	777.5198	111	2404
inc_o	32	62839.06	49731.17	2161	141572

The table comprises the description of variables used in the study. The summary statistics of the input and output variables are shown in figure 2.1 Input and Output Variables of DEA Model

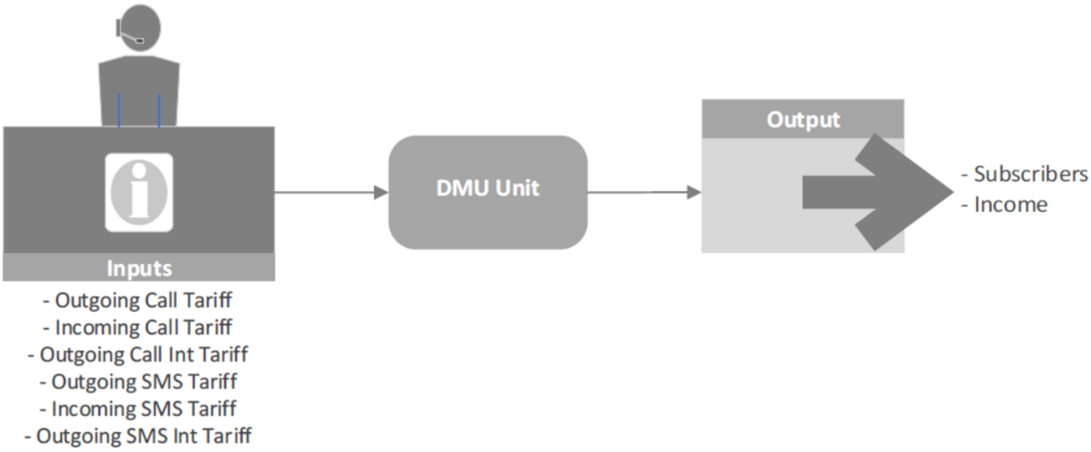

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Table 3: In the period 2009-2016, four firms received an average subscriber 1089.156 and their total income 62839.06 XFA per year. These are produced from average outgoing call tariff 54.8125 XFA, incoming call tariff 82.59375 XFA, outgoing international call tariff 112.0938 XFA, outgoing SMS tariff 14.8125 XFA, incoming SMS tariff 32 XFA and outgoing sms international tariff 68.78125 XFA.

2.2 Efficiency Scores of DEA Model and FDH Model

(1) Efficiency Scores of CRS Output-Oriented Model

The raw data can be imported into the measurement software EMS1.3, and the CRS output-based performance score can be obtained, as shown in the following table 7-4.

Table- 4 Efficiency Scores of CRS Output-Oriented Model

DMU No	DMU Name	Efficiency Score	DMU No	DMU Name	Efficiency Score
1	MTN2009	0.764	17	WARID2009	1.000
2	MTN2010	0.983	18	WARID2010	0.768
3	MTN2011	0.616	19	WARID2011	1.000
4	MTN2012	0.876	20	WARID2012	1.000
5	MTN2013	1.000	21	WARID2013	1.000
6	MTN2014	0.561	22	WARID2014	1.000
7	MTN2015	0.847	23	WARID2015	0.776
8	MTN2016	1.000	24	WARID2016	0.511
9	AIRTEL2009	0.415	25	AZUR2009	0.637
10	AIRTEL2010	0.457	26	AZUR2010	0.457
11	AIRTEL2011	0.805	27	AZUR2011	0.682

12	AIRTEL2012	1.000	28	AZUR2012	0.821
13	AIRTEL2013	1.000	29	AZUR2013	0.391
14	AIRTEL2014	1.000	30	AZUR2014	0.949
15	AIRTEL2015	1.000	31	AZUR2015	0.605
16	AIRTEL2016	0.411	32	AZUR2016	1.000

According to the efficiency score of CRS Output-Oriented Model, the average efficiency scores of four telecom companies in 2009-2016 can be obtained, as shown in the following figure.

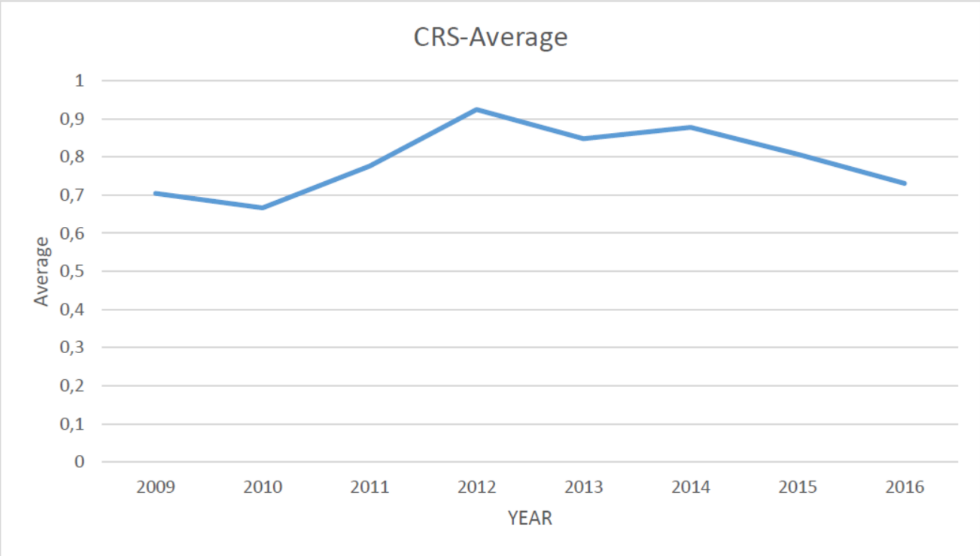

Figure- 3 Average DEA Efficiency Scores of CRS Output-Oriented Model

(2) Efficiency Scores of VRS Output-Oriented Model

The raw data can be imported into the measurement software EMS1.3, and the VRS output-based performance score can be obtained, as shown in the following table 7-5.

Table- 5 Efficiency Scores of VRS Output-Oriented Model

DMU No	DMU Name	Efficiency Score	DMU No	DMU Name	Efficiency Score
1	MTN2009	1.000	17	WARID2009	0.882
2	MTN2010	0.789	18	WARID2010	0.883
3	MTN2011	0.623	19	WARID2011	1.000
4	MTN2012	0.476	20	WARID2012	0.902
5	MTN2013	1.000	21	WARID2013	0.939
6	MTN2014	1.000	22	WARID2014	0.831
7	MTN2015	1.000	23	WARID2015	0.746
8	MTN2016	1.000	24	WARID2016	1.000
9	AIRTEL2009	1.000	25	AZUR2009	0.803
10	AIRTEL2010	0.906	26	AZUR2010	0.979
11	AIRTEL2011	1.000	27	AZUR2011	1.000
12	AIRTEL2012	1.000	28	AZUR2012	1.000
13	AIRTEL2013	1.000	29	AZUR2013	0.675
14	AIRTEL2014	0.641	30	AZUR2014	0.668
15	AIRTEL2015	1.000	31	AZUR2015	0.590
16	AIRTEL2016	0.641	32	AZUR2016	0.761

According to the efficiency score of VRS Output-Oriented Model, the average efficiency scores of four telecom companies in 2009-2016 can be obtained, as shown in the following figure.

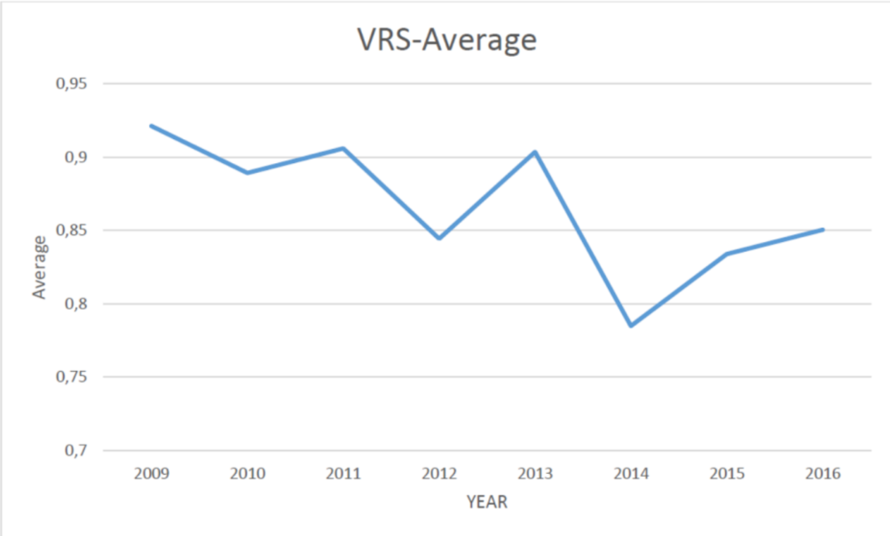

Figure- 4 Average DEA Efficiency Scores of VRS Output-Oriented Model

(3) FDH Efficiency Scores of Output-Oriented Model

Enter the raw data in the measurement software to obtain an output-based performance score, as shown in the table below.

Table- 6 FDH Efficiency Scores of Output-Oriented Model

DMU No	DMU Name	Efficiency Score	DMU No	DMU Name	Efficiency Score
1	MTN2009	0.510	17	WARID2009	1.000
2	MTN2010	0.767	18	WARID2010	0.893
3	MTN2011	1.000	19	WARID2011	1.000
4	MTN2012	0.939	20	WARID2012	0.606
5	MTN2013	0.792	21	WARID2013	1.000
6	MTN2014	0.639	22	WARID2014	1.000
7	MTN2015	0.803	23	WARID2015	0.853
8	MTN2016	0.664	24	WARID2016	1.000
9	AIRTEL2009	0.851	25	AZUR2009	0.757
10	AIRTEL2010	0.658	26	AZUR2010	0.767
11	AIRTEL2011	1.000	27	AZUR2011	0.952
12	AIRTEL2012	1.000	28	AZUR2012	0.844
13	AIRTEL2013	0.786	29	AZUR2013	0.723
14	AIRTEL2014	0.962	30	AZUR2014	1.000
15	AIRTEL2015	1.000	31	AZUR2015	1.000
16	AIRTEL2016	1.000	32	AZUR2016	0.725

According to the efficiency score of FDH Output-Oriented Model, the average efficiency scores of four telecom companies in 2009-2016 can be obtained, as shown in the following figure.

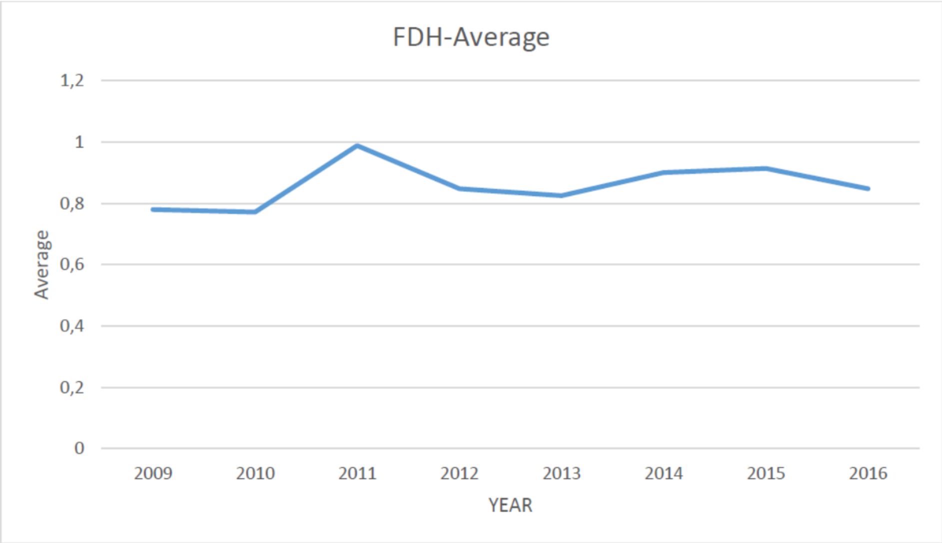

Figure- 5 Average Efficiency Scores of FDH Output-Oriented Model

In addition, we can compare the three types of performance scores and draw the graph as shown below.

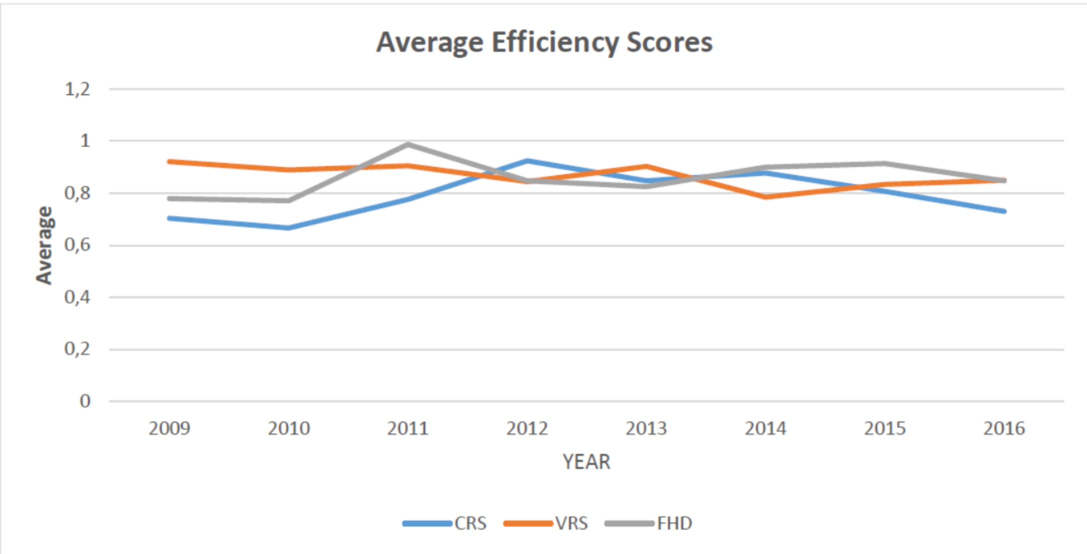

Figure- 6 Comparison of Average DEA, FDH Efficiencies Scores -Output-Oriented Model

The current study bootstrapped DEA scores sing Simar and Wilson's (1998) double bootstrap algorithm of 2000 replications. A graphical demonstration of the bootstrap histogram can represent the shape of the bootstrap distribution. The bootstrap distribution is constructed from the distribution of means from each resample. The bootstrap distribution should have a normal distribution (Minitab, 2018). If the bootstrap distribution is not normal, we cannot trust the result. Figure- shows the bootstrap distribution which is normally distributed, and it implies to reliable result.

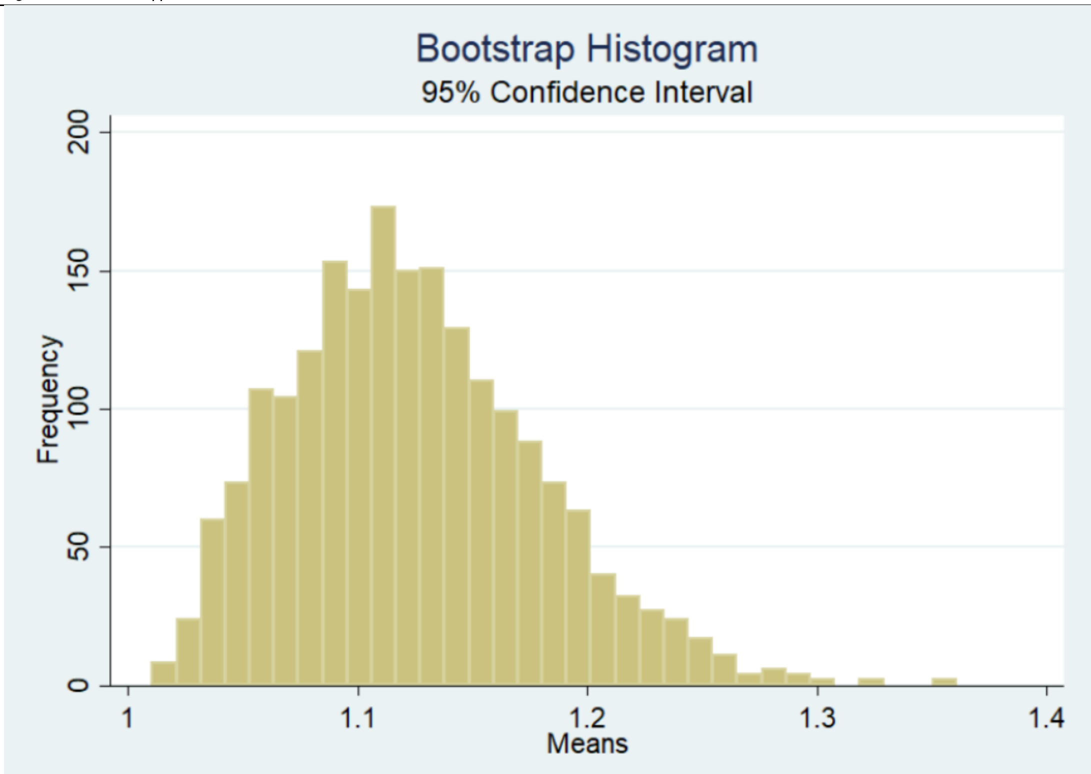

Figure- 7 Bootstrap Distribution

The mean value of bootstrapped DEA scores should be near to the original sample's mean value. In order to bootstrap, the researcher used VRS efficiency scores, and the statistical description of the bootstrap sample and the original sample are given below:

Table- 7 Descriptive Statistics of Bootstrap Sample and Original Sample

Bootstrap Sample					Original Sample				
Obs	Mean	Std. Dev.	95% Conf.	Interval	Obs	Mean	Std. Dev.	95% Conf.	Interval
2,000	1.1243	0.0012	1.1219	1.1266	32	1.1249	0.0550	1.0129	1.2370

Table- 7 shows the mean value of bootstrap and original sample 1.1243 and 1.1249 respectively. Bootstrap mean and sample mean should be theoretically equal to the sample mean otherwise sample bias would not be possible to reduce (Hall, 2013). In the light of the above result, we can see bootstrap mean almost equal to the sample mean.

The mean of the bootstrap sample is an approximation of the population mean because the mean based on sample data rather than based on the entire population. It is unlikely that the sample means equals the population mean (Minitab, 2018). In this case, the confidence interval is the better estimation. Besides, the confidence intervals are calculated by the sampling distribution of a statistics. As an estimator of a parameter if a statistic has no bias, then its sampling distribution is centered at the true value of the parameter. A bootstrapping distribution estimates the sampling distribution of the statistic. Therefore, the middle 95% of values from the bootstrapping distribution provide a 95% confidence interval for the parameter. The practical significance of the estimated population parameter can accessed by a confidence interval. From the above result, we can see the estimated approximate population mean 1.1243. It implies that we can 95% confident that the population mean is between approximately 1.12 and 1.13 (See Table- 7).

2.3 Cross-sectional Study: Technical Efficiency Scores from DEA and FDH Methods

The purpose of this section is to discuss the cross-sectional study. The result obtained from output-oriented DEA and FDH model for the period 2009-2016. The results are shown in Table- 8. The average efficiency score (156%) for the CRS model in 2010 indicates that the firm could have produced an average of 56% more outputs from the currently available input level and remained efficient. Moreover, it is noted that the average efficiency score fluctuated over the year. It means that firms do not have much control on efficiency scores. Therefore, FDH efficiency scores have an almost same trend of VRS. A graphical comparison of average DEA and FDH scores are shown in the Error! Reference source not found.

Table- 8 Average Efficiencies from Cross-Sectional Study

Year	CRS	VRS	FDH
2009	4.80714	1.2003	1.1154
2010	1.56421	1.0000	1.0000
2011	3.57319	1.0000	1.0000
2012	2.41255	1.0150	1.0000
2013	1.46204	1.0828	1.0268
2014	1.41610	1.0286	1.0000
2015	1.88851	1.4347	1.0217
2016	1.72928	1.2381	1.0665

The comparison of efficiency scores for all firms from DEA and FDH model is shown in Table- 9. DMU number from 1 to 8 represents the MTN Company for the period 2009 to 2016. Similarly, DMU number from 9 to 16 represents for AIRTEL Company, from 17 to 24 for WARID and from 25 to 32 for AZUR Company. Since the current study is investigating the impact of price innovation on the performance of telecommunication industry; this is why the study focus on only output-oriented DEA model.

Table- 9 Comparison of DEA, FDH Efficiencies of Output-Oriented Models from Cross- Sectional Study

DMU No.	DMU Name	CRS	VRS	FDH	DMU No.	DMU Name	CRS	VRS	FDH
1	MTN2009	1.73	1.45	1.21	17	WARID2009	5.58	1.00	1.00
2	MTN2010	1.00	1.00	1.00	18	WARID2010	1.00	1.00	1.00
3	MTN2011	1.00	1.00	1.00	19	WARID2011	3.23	1.00	1.00
4	MTN2012	1.02	1.01	1.00	20	WARID2012	1.77	1.00	1.00
5	MTN2013	1.00	1.00	1.00	21	WARID2013	1.06	1.00	1.00
6	MTN2014	1.00	1.00	1.00	22	WARID2014	1.56	1.11	1.00
7	MTN2015	1.00	1.00	1.00	23	WARID2015	1.98	1.00	1.00
8	MTN2016	1.00	1.00	1.00	24	WARID2016	2.09	1.00	1.00
9	AIRTEL2009	1.79	1.35	1.25	25	AZUR2009	10.12	1.00	1.00
10	AIRTEL2010	1.00	1.00	1.00	26	AZUR2010	3.26	1.00	1.00
11	AIRTEL2011	1.00	1.00	1.00	27	AZUR2011	9.06	1.00	1.00
12	AIRTEL2012	1.06	1.05	1.00	28	AZUR2012	5.79	1.00	1.00
13	AIRTEL2013	1.44	1.33	1.11	29	AZUR2013	2.35	1.00	1.00
14	AIRTEL2014	1.00	1.00	1.00	30	AZUR2014	2.10	1.00	1.00
15	AIRTEL2015	1.20	1.20	1.09	31	AZUR2015	3.37	2.54	1.00
16	AIRTEL2016	1.18	1.17	1.17	32	AZUR2016	2.65	1.78	1.00

Demonstrated efficiency scores in Table -9 are based on output-oriented models where a higher number indicates higher inefficiency. It is found that efficiency scores are obtained from FDH model, are found more efficient compare to the CRS and VRS models. Because FDH model reduces the convexity assumption in the efficiency frontier estimation (Radhakrishnan, 2014). On the other hand, FDH compares the hospitals with a real counterpart while estimates the frontier as a linear convex combination of efficient hospitals. More firms are identified to be efficient because it is a direct comparison with another firm by dominance principle. This efficiency scores will be helpful for firms by comparing directly with other firms to change the firms' management.

2.4 Tobit Regression Result Analysis

(1) Descriptive Statistics of Variables Regressed in Tobit Model

Table- 10 Descriptive Statistics of Dependent and Independent Variables

Variable	Observation	Mean	Std. Dev.	Min	Max
inefficiency	32	-0.07	0.15	-0.61	0.00
workers	32	3.22	0.35	2.77	3.95
power out	32	0.03	0.18	0.00	1.00
small	32	0.19	0.40	0.00	1.00

large	32	0.63	0.49	0.00	1.00
domestic	32	0.50	0.51	0.00	1.00
government	32	0.25	0.44	0.00	1.00
int_2g	32	0.69	0.47	0.00	1.00
int_3g	32	0.28	0.46	0.00	1.00

Table -10 shows the average value of inefficiency is -0.07 which is dependent variables. On the other hand, average value of independent variables is 3.22; 0.03, 0.19; 0.63; 0.50; 0.25; 0.69; 0.28 for workers, power out, small, large, domestic, government, int_2g and int_3g respectively. Meanwhile minimum and the maximum value are 0 and one except workers because those all are binary dummy variables.

(2) Tobit Regression Analysis

In the third stage, Tobit regression model employed to find out the variable effect on inefficiency score. The result of Tobit regression model is presented in Table- 11. In order to correct for possible bias, VRS efficiency scores are generated in the second phase, and the normalized inefficiency scores are examined in contrast to the right-side variable as shown in equation (3.1). The previous researcher recommends that a VRS output model is more appropriate if the firm has more control of their outputs as compared to their inputs and they do not always operate at the optimal scale.

Table- 11 Tobit Regression Estimation for VRS Output-Oriented Model

VARIABLES	Inefficiency	VARIABLES	Inefficiency
power out	-0.08811	government	-0.23617***
	(0.14298)		(0.08097)
small	0.01368	int_2g	-0.08662
	(0.07666)		(0.14246)
large	-0.24430***	int_3g	-0.02551
	(0.06937)		(0.13956)
domestic	-0.08325	Constant	0.20532
	(0.06496)		(0.25168)
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1			

A positive value of the estimation indicates a decrease in efficiency because the dependent variable is inefficiency score. The coefficient of the dummy variables can be interpreted as percentage shifts in the inefficiency scores. Two out of seven variables are found statistically significant at the significant level 0.05. The negative coefficient of large indicates that large firm is more likely efficient than a small firm. The results also show that government ownership based firm is more likely to be efficient than the domestic ownership based firm.

Conclusion

This study was the subject of a deep analysis of the study. It methodically and concretely retraced all the points of the analysis, starting with the qualitative study and ending with a quantitative analysis. It also talked about the calculation models and the analysis data. It analyzed the data of the study through different models of analysis. It chapter has therefore spoken of 4 models of analysis to determine the impact of price innovation on the performance of companies in the telecommunication industry in Congo Brazzaville. The study provides information on the finding of the study. Precisely, results include insights on descriptive analysis, correlation analysis, reliability analysis factor analysis and regression analysis. It starts with the presentation of descriptive statistics; normality tests have been conducted to ensure the normality of the data. DEA and FDH analysis have been run to show the relationships between the variables and determine efficiency. Factor analysis has been constructed to ensure the construct validity, and Tobit regression model employed to find out the variable effect on inefficiency score. Indeed, the results of this analysis suggest that the telecommunications sector in Congo or at least the price in this sector impact on the performance of these companies. And the analysis has declined by FDH gives a significant efficiency on the performance of telecommunications in Congo. In doing so, the DEA model that enabled the analysis shows efficient business price and above all, valid the variables represented in the analysis to determine performance.

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APPENDIXES

APPENDIXE A EFFICIENCY SCORES FROM DEAP2.1

A1. Efficiency Scores of CRS Output-Oriented Model from DEAP2.1

```
telecom.txt             DATA FILE NAME
telecom.out             OUTPUT FILE NAME
32            NUMBER OF FIRMS
4                NUMBER OF TIME PERIODS
6        NUMBER OF OUTPUTS
2        NUMBER OF INPUTS
1                0=INPUT AND 1=OUTPUT ORIENTATED
0       0=CRS AND 1=VRS
0                0=DEA(MULTI-STAGE), 1=COST-DEA, 2=MALMQUIST-
DEA, 3=DEA(1-STAGE), 4=DEA(2-STAGE)
```

Figure A- 1 CRS Output-Oriented Model from DEAP2.1 (1)

```
DEAP Version 2.1
****************

A Data Envelopment Analysis (DEA) Program

by Tim Coelli
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The licence for this copy of DEAP is a:
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    for staff and students at

    *** THE UNIVERSITY OF NEW ENGLAND ***

Enter instruction file name: hb.ins.txt
```

Figure A- 2 CRS Output-Oriented Model from DEAP2.1 (2)

EFFICIENCY SUMMARY:

firm	crste	vrste	scale
1	0.764	0.949	0.805
2	0.983	0.996	0.987
3	0.616	0.768	0.802
4	0.876	0.942	0.930
5	1.000	1.000	1.000
6	0.561	0.656	0.855
7	0.847	0.854	0.992
8	1.000	1.000	1.000
9	0.415	0.569	0.729
10	0.457	0.517	0.884
11	0.805	1.000	0.805
12	1.000	1.000	1.000
13	1.000	1.000	1.000
14	1.000	1.000	1.000
15	1.000	1.000	1.000
16	0.411	0.525	0.783
17	1.000	1.000	1.000
18	0.768	0.809	0.950
19	1.000	1.000	1.000
20	1.000	1.000	1.000
21	1.000	1.000	1.000
22	1.000	1.000	1.000
23	0.776	0.578	1.342
24	0.511	0.460	1.110
25	0.637	0.770	0.827
26	0.457	0.328	1.392
27	0.682	0.755	0.903
28	0.821	0.921	0.891
29	0.391	0.510	0.766
30	0.949	1.000	0.949
31	0.605	0.681	0.888
32	1.000	1.000	1.000

Figure A- 3 CRS Output-Oriented Model from DEAP2.1 (3)

B2. Efficiency Scores of VRS Output-Oriented Model from DEAP2.1 Figure

```
telecom.txt              DATA FILE NAME
telecom.out              OUTPUT FILE NAME
32           NUMBER OF FIRMS
4               NUMBER OF TIME PERIODS
6         NUMBER OF OUTPUTS
2         NUMBER OF INPUTS
1               0=INPUT AND 1=OUTPUT ORIENTATED
1        0=CRS AND 1=VRS
0               0=DEA(MULTI-STAGE), 1=COST-DEA, 2=MALMQUIST-
DEA, 3=DEA(1-STAGE), 4=DEA(2-STAGE)
```

Figure A- 4 VRS Output-Oriented Model from DEAP2.1 (1)

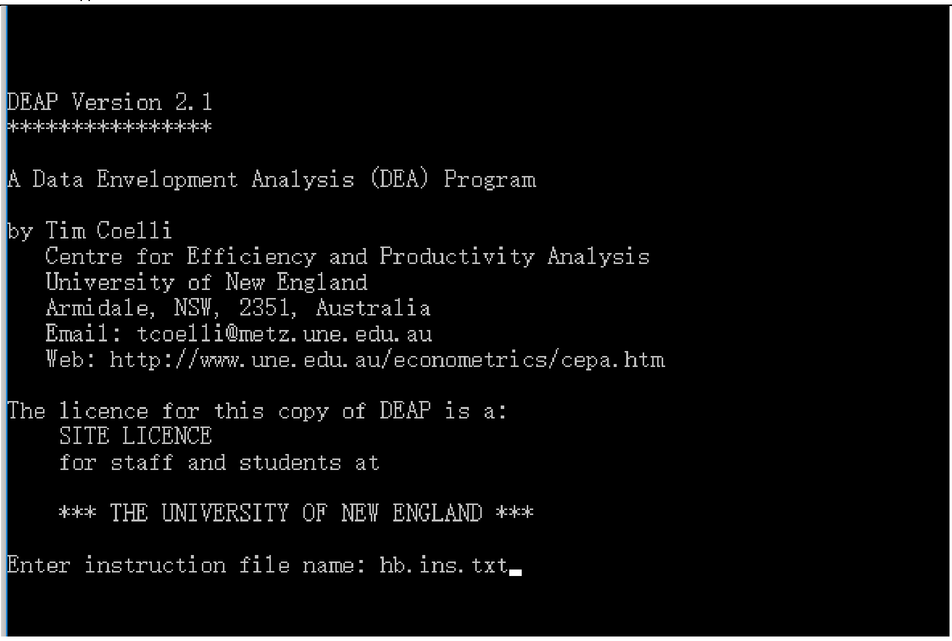

Figure A- 5 VRS Output-Oriented Model from DEAP2.1 (2)