A Two-Stage Performance Improvement Evaluation of the Insurance Industry in Kenya: An Application of Data Envelopment Analysis and Tobit Regression Model.

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Abstract

The study applies two stage Data Envelopment Analysis (DEA) to evaluate efficiency of insurance firms in Kenya from 2011-2014. The objectives of this study were therefore to

a) Establish the relative performance efficiency levels of the Kenya's insurers
b) Determine the improvement potential of inefficient insurance firms to render the inefficient company to attain efficiency frontier
c) Assess the significance of the drivers of the firm's relative efficiency. The inputs employed were
   i. Total commissions and other expenses
   ii. Shareholders capital life fund & reserve and
   iii. Total assets. On the output side, the variables used were
      - Net earned premium
      - Investment income & other incomes
      - Net incurred claims and
      - Profit/loss after tax.

Regarding study methodology, data envelopment analysis is employed stage one to establish the insurers' efficiency scores. In stage two, tobit regression analysis is applied to evaluate endogenous drivers of efficiency. Data used for the study is obtained from the Association of Kenyan Insurers (AKI) reports from 2011 – 2014. Prior to in-depth analysis, the data was cleaned using standard procedures. In addition, a constant number was added to the output data to correct for negative values in compliance with DEA methodological requirements. The study found that of the 42 insurers investigated, 55% attained the efficiency frontier in 2011, 33% in 2012, 19% in 2013 and 36% in 2014. In addition, the results show that a number of insurers were employing their inputs effectively and judiciously in producing the existing level of output. Regarding the second stage using tobit regression, it was found that there is a positive relationship between net incurred claims, total assets and profit after tax and e overall efficiency score. On the other hand, total commissions & other expenses; shareholders capital life fund & reserve; net earned premium and investment income & other incomes negatively affect efficiency levels. In addition, the study found that the coefficients of the variables total commissions & other expenses, shareholders capital life fund & reserve were statistically significant. On slack analysis, results show that, in general the inputs and outputs chosen for evaluating the performance of each inefficient insurer provide critical and useful information about their operating performance objective.

Keywords: Data Envelopment Analysis, Decision Making Units (DMUS), VRS Efficiency, Slack Analysis, TOBIT Regression Analysis

Introduction

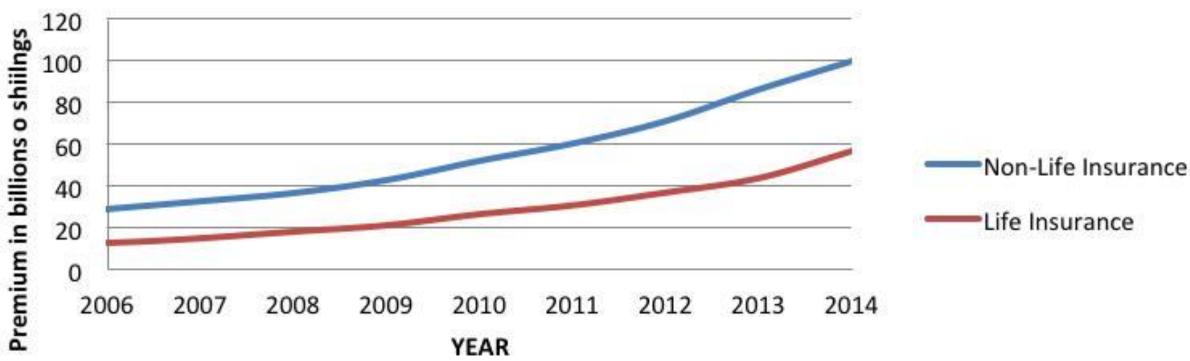
The basic function of insurance is to act as a risk transfer mechanism with the requisite capacity to protect individuals and entities against losses and related consequences (Nandi, 2014). Towards this end, Insurers design services and products that enable them to persuade a critical mass of individuals to pool their risks into a large group to minimize overall risk. In developing countries such as Kenya, the need for such a safety net is much more desired particularly by the poor whose vulnerability to risks is much greater and with fewer options available to recover from large losses. Additionally for majority of developing countries, the problem is further compounded by among others existence low income levels, lack of access to social security systems, invariably poor healthcare and education systems, poor sanitation and limited employment opportunities. The need to provide efficient insurance services is therefore more imperative.

Just as in majority of both public and private sector organizations, evaluation of efficiency of insurance companies, has in the recent times received increased research attention. This situation has, however been more pronounced in developed economies where insurance is a more sophisticated and highly integrated in society. This unlike in developing economies where coverage has remained restricted to significantly smaller percentage of the population leaving a larger and poorer segment largely uncovered. According to Shahroudi, et.al. (2012), insurance sector’s role is to complement the governmental social actions, especially amongst the poor, by providing individuals with services that guarantees them with safety nets and confidence. Efficiency objective in the sector are thus intended to enable the firms increase quality of their activities in a manner that assists them to identify and solve problems of low productivity.

In Kenya, while the performance of the sector has evidently been quite impressive (Figure 1), the industry has to a large extent also be characterized with increasing cost of doing business. For example, according to the Association of Kenya Insurers (2014), the total expenses (total operating and other expenses) incurred in 2014 for insurance Life insurance (Ordinary and Group Life) was Kshs. 9.37 billion compared to Kshs. 7.35 billion in 2013, an increase of 27.5%. Additionally, commission expenses for Ordinary and Group Life in 2014 amounted to Kshs. 3.83 billion compared to Kshs. 3.17 billion in 2013, an increase of 20.8%. The scenario has, in part, been attributed to the operating environment and the efficiency related factors such the sub-optimal use of inputs to generate expected outputs.

There is therefore an urgent need to evaluate the efficiency of the sector with a view to exploiting the available improvement potentials. This taking cognisance of the fact by 2014 that the sector comprised of 49 operating insurance companies consisting of 25 companies writing non-life insurance business only, 13 writing life insurance business only and 11 writing a composite of both

Figure 1: Gross Written Premium for the Period 2006 – 2014



The growth of the insurance sector in Kenya, at least at micro-level has continued to elicit debate on whether this performance is accompanied with efficient use of scarce resource to produce the much needed output. Questions have also arisen as to whether the apparent exemplary performance of the industry in Kenya compared to its continental counterparts has been matched with acceptable quality of services and effective cost control mechanisms. This has led to the need to evaluate the efficiency of the insurers to generate information that may be used to improve their performance. Further, it is also clear that like in majority of Sub-Saharan African countries save for Nigeria and South

Africa, invariably fewer efficiency studies have been undertaken in the sector, more so using standard methodologies such as nonparametric Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Analysis (SFA).

To this extent, this study is further designed to contribute to empirical literature by addressing this gap. In addition, to our knowledge this is the first study that focuses on efficiency and its drivers in

Kenya using the two stage methodology. The objectives of this study are therefore a) to establish the relative performance efficiency levels of the insurance firms in Kenya b) determine the improvement potential of inefficient Insurance firms and c) assess the endogenous drivers of the firms' relative efficiency levels.

1 Review of Related Literature

The two-stage methodology for performance evaluation has been used widely in the assessment of efficiency of productive units technically called decision making units (DMUs) in DEA studies. According to Liu, et., al (2012), this procedure has been found most useful in evaluating the technical efficiency especially where the concern it to optimize the use of inputs to maximize output levels subject to given sets of constraints. Through this approach, efficiency scores are first derived using an appropriate Data Envelopment Analysis variant in stage one. This is then followed by an application of tobit or logit or probit regression to analyse factors (either exogenous or endogenous or both) affecting efficiency levels of target firms.

2.1 Frontier Efficiency Methodologies

2.1.1 Related Theoretical Literature

The two main methodologies used in efficient frontier analysis are the econometric (parametric) and the mathematical programming (nonparametric) approaches (Banker et al. (1989), Charnes et al. (1994), Berger & Humphrey (1997), Cummins & Weiss (2000) and Cooper, Seifor & Tone (2007).

Studies on econometric (parametric) approaches indicate that these methodologies require specification of some a production, cost, revenue, or profit function form with a specific shape with clear assumptions. According to Cummins and Weiss (2000), all the principal types of parametric frontier approaches usually specify an efficient frontier form, but only differ in their distributional assumptions of inefficiency and corresponding random error components. These parametric approaches are the stochastic frontier approach (SFA) which assumes a composed error model with inefficiencies following an asymmetric distribution, the distribution-free approach (DFA) which has fewer underlying assumptions and the thick frontier approach (TFA) which according to Berger & Humphrey (1997) does not make any distributional assumptions on the random error and inefficiency terms. Unlike the aforementioned parametric approaches, mathematical programming models place limited structure on the specification of the efficient frontier. In addition, the models allow for the inefficiency and error terms decomposition. Of the available mathematical programming approaches, the most widely used model is the data envelopment analysis (DEA). DEA uses linear programming techniques to evaluate the relationship between outputs (produced goods and services) and inputs (resources). Being an optimization technique, DEA finds an efficiency score which can sometimes be interpreted as a performance measure. First introduced by Charnes, Cooper and Rhodes (1978) by building on the method suggested by Farell (1957), DEA was designed for the computation of efficiency scores relative to some reference point. These models can be specified under two main assumptions; the assumption of Constant-Return-to Scale (CRS) or Variable-Returns to Scale (VRS). According to Cummins and Weiss (2000) DEA under whatever assumption can be used to decompose cost efficiency into its single components technical, pure technical, allocative, and scale efficiency.

While, in the past, the nonparametric frontier methodologies have found wide use in the banking and non-financial sectors, there is also evidence of their increased use of in the insurance field. This in addition, to the two –stage methodologies that are designed for the assessment of the effect selected factors on efficiency levels as used by for example Malaysiana (2014), Oberholzer (2014), Wankeand Barros (2016), Micajkova (2015) and Pawar (2015).

2.1.2 Related Empirical Literature

Barros & Obijaku (2007) analyzed the technical efficiency of ten Nigerian insurers in Nigeria. The study employed four DEA models DEA-CCR, DEA-BCC, Cross efficiency DEA model, Super efficiency DEA model. Both technical and scale efficiencies were derived using the four DEA models followed by Mann-Whitney U test in the second stage. Outputs were net premium, settled claims, outstanding claims, investment income. Inputs were total capital, total operative costs, total number of employees, total investment. DEA CCR and BCC model were found to be strong in identifying efficient units but failed to discriminate between the inefficient units. Additionally, the study found that Nigerian insurers were managed with pure technical efficiency and for technically inefficient insurers there was room to upgrade their efficiency level by means of reference to their peers.

Malaysiana (2014) used the two stage methodology of DEA and tobit regression to assess the effect of the exogenous variables of risk and investment management on efficiency of the Malaysian insurance firms. The study treated the efficiency scores obtained through DEA as the dependent variable, while the exogenous factors of operating systems, organizational form, consumer preference and size were used as independent variables. The study found that mutual companies and the Takaful systems demonstrated better risk management performance than the stock and conventional system counterparts. In addition, except for consumer preference, size of the firm was found to significantly affect efficiency. In contrast, regarding risk management, factors such as organizational form, operating system and size were found not to be statistically significant drivers of efficiency.

Saad and Idris (2011) study focused on the performance of insurance industry in Malaysia and Brunei by making comparison on the efficiency of life insurance companies in the Malaysia and Brunei for the year 2000-2005 by using DEA. The study utilized two inputs namely commission agents and management expenses and two outputs namely premium and net investment income. Findings indicated that the bigger the size of the company, the higher the profitability for the companies to be more efficient in utilizing their inputs to generate more outputs. Due to the positive impact of both efficiency and technical changes the overall total factor productivity for these firms was maintained at a value higher than one.

Sabet and Fadavi (2013) measured the performance of insurance firms which were active in Iran over the period of 2006-2010 with the help of two stage data envelopment analysis. In stage one, DEA efficiency scores were derived using operating costs, insurance costs, number of employees, number of branches and central offices and number of agents as inputs and direct insurance, number of insurance certificates and complementary insurance as Outputs. This was followed by stage two where outputs of first stage were used as inputs and outputs in this stage being income from sale of insurances, short term and long term investment returns and market share. The study measured the relative efficiencies over the period of 2006-2010 by firstly calculating the efficiency of the firms independently at two stages and then multiply this number together to get the overall efficiency. The survey results indicated that the average efficiency of insurance firms in all years was relatively low which means limited number of units dominated the market compared with other insurance firms. Additionally, the results indicated that majority of the firms were noticeably inefficient implying that the Iranian insurance market was monopolized mostly by a limited number of insurance firms and competition was not fair enough to let other firms participated in economy more efficiently.

Micajkova (2015) measured the technical, pure technical and scale efficiency of 11 Macedonian insurance companies using Data Envelopment Analysis (DEA) according to both the Char¬nes, Coo¬per and Rho¬des (CCR) and Banker-Charnes-Cooper (BCC) output-oriented model. Covering the period 2009-2013, the study found that on average, there was an increase in efficiency over the target period. The same trend was observed regarding scale efficiency. In addition, the efficiency score from BCC model was higher than in the CCR case, implying that the main source of inefficiency was due to scale inefficiencies. The study did not however failed to address issues related to the determinants of the derived efficiency or inefficiencies.

Baros & Wanke (2016), in their study of the Brazilian insurance industry investigated the role of heterogeneity in the insurance sector using a balanced panel data set on Brazilian insurance companies. Applying a two stage methodology, the study found that the hypothesised underlying heterogeneity of the industry had a significant impact on efficiency. In addition, it was found that overall efficiency levels in the Brazilian insurance sector were significantly high with a minimum value of 0.806. This study adopted an output maximisation orientation by assuming that decision-makers attempt to maximise production outputs. Taking into account that the main objective of insurance companies in Brazil was to maximise revenues using existing inputs in the context of a competitive market, the use of an output-oriented model was found suitable for this analysis a finding which was in line with previous studies.

3 Data and Methodological Framework

The section presents the study data and methodological framework with the latter focusing on Data. Envelopment Analysis to derive the efficiency scores and accompanying improvement potentials (slacks) as the first stage and the Tobit (Censored) regression methodology to assess the effect of the endogenous drivers of efficiency as stage two.

3.1 Data Source and data

Data source for this study was the Association of Kenya Insurers (AKI) annual reports from 2011 –2014. The entire population of 49 insurance firms was initially selected. However due to issues of data completeness on the selected input and output variables, the number of firms were subsequently limited to 42 firms. Additionally, given that some of the output variables had negative values, a constant number was added to convert them to positive values to enable the use of DEA methodology to derive the efficiency scores

3.2 Data Envelopment Analysis (DEA) Methodology

The study employed the nonparametric Data Envelopment Analysis (DEA) methodology to derive the required efficiency scores in stage one. To estimate the insurers' efficiency scores, three inputs and four output variables were used. After Farrell (1957), Charnes, Cooper and Rhodes (1978) were the first to introduce the term DEA (Data Envelopment Analysis) to describe a linear programming technique for developing production frontiers and efficiency measurements corresponding to these constructed frontiers. The latter authors proposed an input orientation model which assumed constant returns-to-scale (CRS) and commonly known in literature as CCR model. Variants of the DEA model were later developed by considering alternative sets of assumptions. For example Banker, Charnes and Cooper (1984) by introducing the assumption of variable returns to-scale (VRS) developed a model commonly referred to literature as the BCC model. The other DEA models developed in later years but with infrequent use were the multiplicative model of Charnes et al.(1982), the additive model of Charnes et al. (1985), the Cone-Ratio DEA model of Charnes et al. (1990) and the Assurance-Region DEA model of Thompson et al. (1990).

In DEA modelling, to solve the defined linear-programming problem, the analyst must specify three critical components of the model: the input-output orientation system, the appropriate returns-to-scale and the relative weights of the evaluation. The decision to use either the input or output orientation is a function of the market condition of the Decision Making Unit (DMU). For competitive markets such as insurance markets, the DMUs are output-oriented since it is assumed that inputs are under the control of the DMU (in this case the insurer) which aims to maximize its output subject to market demand that is invariably outside the control of the DMU. Conversely, in monopolistic markets, the units analyzed (DMU) are input-oriented because the output is endogenous in this market while the input is exogenous therefore the cost function would be the natural choice. The input-orientation system searches for a linear combination of the DMUs that maximizes the excess input usage of the DMU subject to the defined inequality constraints. With regard to returns-to-scale, these may be either constant or variable. Regarding the relative weights, that are used with inputs and outputs in the objective function, these are also subject to the same inequality constraints and are defined endogenously by the algorithm to measure the distance between the DMU and the efficiency frontier.

3.2.1 DEA Model Specification

Formal notations used under the input-oriented DEA models for measuring efficiency scores for DMUo, under different scale assumptions are as follows.

$$\min_{(\theta_0,\lambda_1,\lambda_2,\lambda_3,S^-,S^+)} \quad TE = \theta_0 - \xi\left(\sum_{i=1}^{m} S^-{}_i + \sum_{r=1}^{r} S^+{}_r\right)$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} + S^-{}_i = \theta_o x_{io} \qquad (1)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - S^+{}_r = y_{ro} \qquad (2)$$

$$S^-, S^+ \geq 0 \quad (i = 1,2,3,4 \quad r = 1,2,3) \qquad (3)$$

$$\lambda_j \geq 0 \text{ if CCR assumption} \qquad (4)$$

$$\lambda_j = 1 \text{ if VRS assumption} \qquad (5)$$

Where TE=Technical efficiency; xio = amount of ith input used by oth DMU; yro = amount of rth output used by oth DMU; m=the number of outputs; s=the number of inputs; n= the number of

DMUs (Insurance firms), and = a small positive number.

The constraints (1) and (2) form the convex reference technology. The restriction (3) restricts the input slack or input improvement potential ( ) or and output slack or output improvement potential ( ) variables to be non-negative. The restriction (4) limits the intensity variables ( ) to be non-negative. The above model without restriction (5) is known as envelopment form of CCR model and provides Farrell's input-oriented TE measure under the assumption of constant returns-to-scale. Constraint

(5) Imposes variable returns-to-scale assumption on the reference technology. Hence above model without (4) is known as BCC model and provides Farrell's input-oriented TE measure under the assumption of variable returns- to-scale. The measure of efficiency provided by CCR model is known as overall technical efficiency (OTE) while efficiency provided by

BCC model is known as pure technical efficiency (PTE). The ratio between CCR and BCR efficiency (OTE/PTE) is a measure of scale efficiency.

3.3 Tobit (Censored) Regression Analysis

In stage two, the study used the non-standard ordinary least square (OLE) regression analysis to estimate the level of significance and direction of the effect of a set of internal drivers (inputs and outputs) on efficiency of Kenyan insurance firms. In DEA literature, this analysis usually employs either tobit or logistic regression models because the distribution of efficiency scores is limited to the internal between 0 and 1 inclusive. The nature of this distribution, censored as it were, makes the standard Ordinary Least Square (OLS) regression method to yield inconsistent estimates of regression parameters. Tobit regression (which is used in this study) allows one to predict a censored dependent variable from a set of predictors that may be continuous, discrete, dichotomous, or a mix of any of these.

By letting yi to be the efficiency of the jth insurance firm, x1=total commissions & other expenses; x2=

Share Holders Capital, Life Fund & Reserve, x3=Total assets, x4=net earned premium, x5=investment income & other incomes, x6=net incurred claims and x7=profit after tax), below is the specification of the tobit regression model used in this study

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \varepsilon$$

Where (i=1,2,3….7) is the coefficient of the ith driver whose significance and direction of effect is to be estimated and indicates the error term which is assumed to be normally distributed ( ). The coefficients of the Tobit regression model can be interpreted as is done with the coefficient of an ordinary least squares regression. That is that it indicates the proportionate change of dependent variable with respect to one unit change in independent variables, while holding other factors constant and if negative (positive), then there is an inverse (direct) relationship between efficiency and the ith driver. This study proposed the following seven hypotheses to guide the determination of how the selected endogenous factors affect the technical efficient score of Kenya's insurance firms:

Hypothesis 1: The insurer that has low (high) total commissions & other expenses is likely to have a high (low) efficiency score;

Hypothesis 2: The insurer that has low (high) shareholders capital life fund & reserve is likely to have a high (low) efficiency score;

Hypothesis 3: The insurer that has low (high) total assets is likely to have a high (low) efficiency score;

Hypothesis 4: The insurer that has high (low) net earned premium is likely to have a high (low) efficiency score;
Hypothesis 5: The insurer that has high (low) investment income & other incomes is likely to have a high (low) efficiency score;

Hypothesis 6: The insurer that has high (low) net incurred claims is likely to have a high (low) efficiency score;

Hypothesis 7: The insurer that has high (low) profit after tax is likely to have a high (low) efficiency score.

4 Empirical findings

4.1 Summary output/input Statistics

Among the outputs, better outcome was realized in 2011 as indicated by a mean of 4.53 million for net earned premium, 2.85 million for investment income & other Incomes, 3.71 million for net incurred claims and 2.31 million for profit/(Loss) after tax. This compared with output outcome scenario in 2012 which was apparently the worst year for the industry in Kenya. It is also clear from the results that better output outcome across the years was accompanied by a corresponding higher level of input use as can be seen from for example input use in 2011 against the output achieved.

Table 1: Summary output/input Statistics in millions of Kenya Shillings

			OUTPUT & INPUT VARIABLES				
	O1	O1	O1	O1	I1	I2	I3
2011							
Mean	4.53	2.85	3.71	2.31	3.22	4.20	13.29
Mean	4.53	2.85	3.71	2.31	3.22	4.20	13.29
Standard Deviation	14.56	9.16	11.92	7.40	10.33	13.50	43.68
Minimum	1.00	0.98	0.64	0.84	1.05	1.19	1.31
Maximum	97.30	61.36	79.69	49.65	69.29	90.28	285.74
2012							
Mean	2.65	1.85	2.30	1.27	1.81	2.40	7.59
Standard Deviation	1.92	1.24	1.71	0.51	0.88	1.73	9.34
Minimum	1.01	1.01	1.01	0.38	1.04	0.16	1.00
Maximum	8.38	7.16	8.25	3.47	5.53	8.64	42.04
2013							
Mean	2.89	1.99	2.47	1.34	1.99	2.85	9.36
Standard Deviation	2.29	1.55	2.05	0.63	1.10	2.32	11.87
Minimum	1.01	1.03	1.01	0.26	1.03	1.12	1.39
Maximum	10.16	7.91	10.19	4.18	7.06	10.96	50.24
2014							
Mean	3.42	2.08	2.96	1.27	2.18	3.11	10.94
Standard Deviation	3.21	1.60	3.02	0.37	1.24	2.47	14.30
Minimum	1.02	1.01	1.01	0.55	1.05	1.15	1.45
Maximum	13.97	7.57	14.71	2.56	7.16	11.21	57.11

Key: Outputs (O1= Net Earned Premium, O2= Investment income & Other Incomes, O3=

Net Incurred Claims, 04= Profit/(Loss) After Tax) and Inputs (I1= Total Commissions & Other Expenses,

I2= Share Holders Capital, Life Fund & Reserve and I3= Total Assets)

4.2 Derived BCC Efficiency results

In this study, the BCC DEA model was used to derive efficiency levels of the insurance firms in Kenya. Using year-wise analysis, the performance of insurers was measured under the Variable Return to Scale (VRS) assumption (Table 2).

Table 2: BCC efficiency of Insurance firms

Companies	**2011**	**2012**	**2013**	**2014**	**Companies**	**2011**	**2012**	**2013**	**2014**
AIG	1.000	0.845	0.774	1.000	Kenindia	1.000	0.996	1.000	1.000
Amaco	0.977	0.556	0.684	0.862	Kenya Orient	1.000	0.828	0.771	0.804
APA	1.000	0.930	0.974	0.880	Kenyan Alliance	0.884	0.686	1.000	0.758
Apollo Life	1.000	1.000	0.977	0.907	Madison	0.950	0.986	0.762	0.857
Britam	1.000	0.979	1.000	1.000	Mayfair	0.963	0.844	0.871	0.830
Cannon	0.962	0.783	0.838	0.761	Mercantile	0.924	1.000	0.967	0.867
Capex Life	1.000	1.000	1.000	1.000	Metropolitan Life	0.901	0.792	0.806	1.000
CFC Life	1.000	1.000	0.997	1.000	Monarch	0.935	0.729	0.831	0.886
CIC General	1.000	1.000	1.000	1.000	Occidental	1.000	0.912	0.862	0.919
Corporate	0.925	0.908	0.894	0.909	Old Mutual Life	0.789	0.733	0.655	0.686
Directline	1.000	0.865	0.794	1.000	Pacis	0.995	0.755	0.900	0.883
Fidelity Shield	0.956	0.807	0.807	0.808	Pan Africa Life	1.000	1.000	1.000	1.000
First Assurance	1.000	0.839	0.946	0.912	Phoenix	0.833	0.782	0.854	1.000
GA	0.927	0.795	0.832	0.801	Pioneer Life	1.000	1.000	0.954	1.000
Gateway	1.000	0.789	0.834	0.737	Real	0.988	0.844	0.820	0.919
Geminia	0.917	0.784	0.922	0.831	Shield Assurance	0.999	0.961	1.000	0.976
Heritage	1.000	1.000	0.840	0.878	TakafuI	0.935	0.764	0.765	0.914
ICEA LION Life & General	1.000	1.000	1.000	1.000	Tausi	0.931	0.908	0.963	0.846
Intra Africa	1.000	0.887	0.962	0.915	Trident	1.000	1.000	0.888	0.869
Invesco	1.000	1.000	0.537	1.000	UAP Life & General	1.000	1.000	0.940	0.918
Jubilee	1.000	1.000	1.000	1.000	XpIico	1.000	0.878	0.816	1.000

Additionally, the distribution of the percentage of the insurers lying on the efficient frontier with a score equal to 1 determined (Table 3).

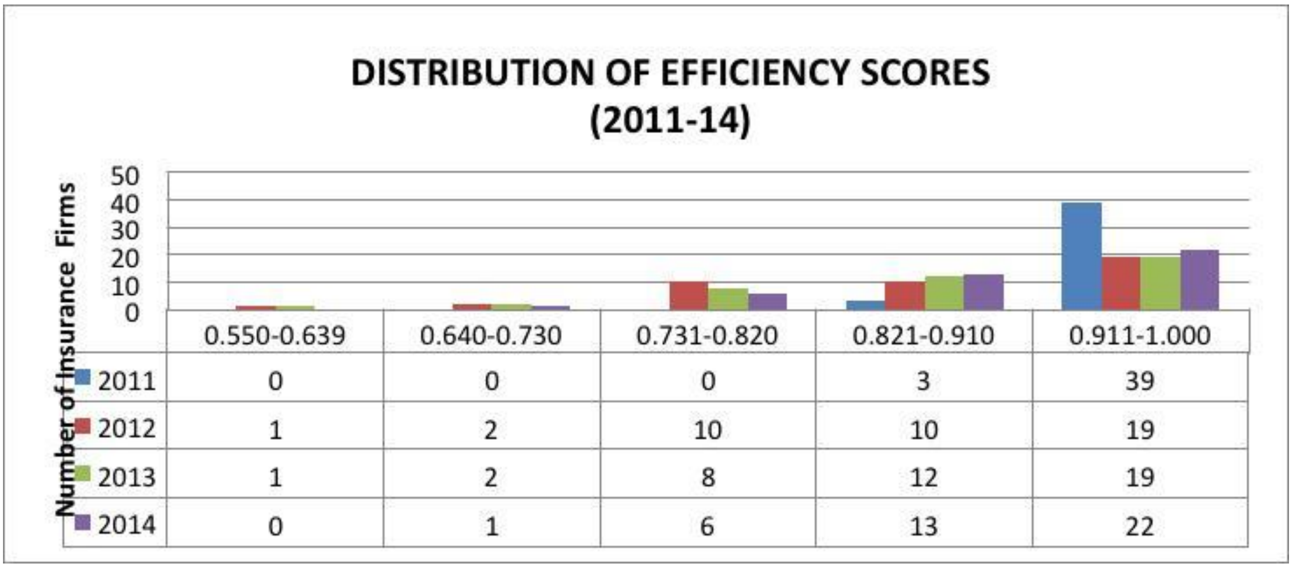
Table 3: Year-wise distribution of insurance firms by performance

	Number (%) of firms	
Year	Lying on efficient frontier	Lying below efficient frontier
2011	23 (55%)	19 (45%)
2012	13 (31%)	29 (69%)
2013	9 (21%)	33 (89%)
2014	15 (38%)	27 (38%)

Results indicate that there was a sharp drop on the percentage of efficient firms from 2011 (55percent) through 2012 (31percent) to 2013(21percent) in 2013 with a slight improvement realized in 2014

(38percent). Compared with the result in Table 2, the findings indicate for example that from 2011 to 2012, companies such as Gateway, First Assurance, Direct line, APA and AIG exhibited poorer performance in 2012 compared to the previous year. A number of were however companies that were inefficient in the previous years but attained the efficient frontier in the following year. For example, Mercantile which had an efficiency score of 0.924 in 2011 attained a score of 1 in the following year, this in spite of the sharp drop in the overall number of efficient firms as can be discerned from 2012 to 2014. Further insight was obtained from the findings regarding the distribution of efficiency scores over the study period (figure 2).

Figure 2: Distribution of efficiency Scores



The nature of skewness of the distribution of the yearly efficiency scores that in Kenya (Figure 2) can be interpreted that majority of the firms lie on or very close to the efficient frontier with this being most pronounced in 2011 compared to 2012-2014. These results are consistent with those exhibited in the summary statistics shown in Table 4 below:

Table 4: Summary Statistics

	YEAR			
Descriptive Statistics Measures	2011	2012	2013	2014
Mean	0.969	0.885	0.882	0.908
Standard Error	0.008	0.017	0.017	0.013
Range	0.211	0.444	0.463	0.314
Minimum	0.789	0.556	0.537	0.686
Maximum	1.000	1.000	1.000	1.000
N	42	42	42	42

4.3 Tobit Regression Results: Second Stage Analysis

Using the Tobit (censored) regression model in section 3.3, this section presents nature of influence of the endogenous organizational input/output variables on efficiency scores. As indicated earlier, by lettering X1 = Net Earned Premium, X2 = Investment income & Other Incomes, X3 = Net

Claims Incurred, X4 = Profit/(Loss) After Tax, X5 = Total Commissions & Other Expenses, X6 = Share Holders Capital Life Fund & Reserve, X7=Total Assets and Y = Efficiency score. Table 5 show the tobit regression results using the model

$$y = \hat{a}_{0} + \hat{a}_{1}x_1 + \hat{a}_{2}x_2 + \hat{a}_{3}x_3 + \hat{a}_{4}x_4 + \hat{a}_{5}x_5 + \hat{a}_{6}x_6 + \hat{a}_{7}x_7 + e$$

Table 5: Tobit regression results

Independent Variables	Coefficient(β0)	Std. Error	Prob.
Constant	0.816894	0.076192	0.000
Net Earned Premium	-1.71E-08	3.50E-08	0.025
Investment income & Other Incomes	-3.73E-08	3.81E-08	0.000
Net Claims Incurred	4.83E-08	4.19E-08	0.046
Profit/(Loss) After Tax	1.29E-07	7.69E-08	0.013
Total Commissions & Other Expenses	-2.11E-08	4.55E-08	0.642
Share Holders Capital Life Fund & Reserve	-2.12E-08	2.17E-08	0.329
Total Assets	2.59E-09	4.72E-09	0.003

It is clear from the above findings that:

a) There is an inverse relationship between efficiency on the one hand and two output variables (net earned premium and investment income & other Incomes) and two input variables (total commissions & other expenses and shareholders capital life fund & reserve).

b) There is a direct relationship between efficiency on the one hand and one output variables (net claims incurred) and two input variables (profit/(loss) after tax and total assets).

The above results are consistent with the earlier hypothesised proposition regarding the relationship between efficiency on the one hand and total commissions & other expenses, shareholders capital life fund & reserve, net incurred claims and profit after tax is. Results do however disprove the nature of relationship between efficiency scores and total assets, net earned premium and investment income & other incomes. Regarding statistical significance of the BETA coefficients, those of total commissions & other Expenses and shareholders capital were not found to be statistically significant while those of the rest of the input and output variables were statistically significant.

4.4 Analysis of Benchmarking Firms

DEA lends itself to multiple input/output analysis where targets are based on observed performances rather than theoretical performances that may not be feasible. The methodology aids in the identification of a set of efficient units (peers or benchmarking units) that are most comparable to the configuration of the inefficient units. In addition, it is a benchmarking technique in the sense that the "best practice" as in this case insurance firms lie on the efficient frontier and "envelop" other inefficient firms. Table 6 shows our results on the distribution of the peer units across the years. These findings are intended to indicate the firms that a) most frequently act as benchmarks across the industry and b) are consistent benchmarking firms across the years.

Table 6: Distribution of benchmarking firms (2011-14)

DISTRIBUTION OF BENCHMARKING INSURANCE FIRMS							
2011		2012		2013		2014	
FIRM	Number	FIRM	Number	Firm	Number	Firm	Number
Britam	3					Britam General	2
Capex Life	11	Capex Life	10	Capex Life	28	Capex Life	16
CIC life and General	9	CIC Life & General	1	CIC Life & General	8	CIC Life & General	10
Corporate	10						
Gateway	16						
Directline	4					Directline	3
Heritage	2	Heritage	5	Heritage	13	CFC Life)	2
		ICEA LION Life	3	ICEA LION General	6	ICEA LION Life & general	2
Invesco	3	Invesco	3	Invesco	7		
Kenindia	2	Kenindia	1	Kenindia	2		
Kenyan Alliance	11	Kenyan Alliance		Kenyan Alliance	28		
Pan Africa Life	6	Pan Africa Life	1	Pan Africa Life	33	Pan Africa Life	8
Pioneer Life	2	Pioneer Life	5	Pioneer Life	10		
Trident	6	Trident	13	Trident	6		
Xpliico	1	Xplico	6	Xplico	7	Xplico	2

The findings indicate that the firms which were consistent benchmark insurance companies from 2011 to 2014 were for example Pan Africa Life, Xplico, CIC life and General and Capex life. On the other hand, ICEA LION Life, Invesco, Kenindia and Pioneer Life were the most referenced firms as can demonstrated by the fact that these firms were peers in three of the four years study period.

Figure 4: Average output Slacks

The implication of efficiency improvement potential is to place the inefficient insurers on the efficient frontier. The slacks for each of the four outputs as per the above findings indicate the level by which the output levels are short of desired targets.

5 Conclusions, Study Limitations and Recommendations

In this paper, we employ both the DEA framework and tobit regression methodology to evaluate the efficiency of Kenya Insurance industry. The analysis is based on the DEA-BCC model, which allows for the use of multiple inputs and outputs in determining relative efficiencies. Additionally, the study uses tobit regression model to assess the endogenous drivers of efficiency scores obtained from DEA. From 2011-2014, we estimate that in 2011, 55percent attained the efficiency frontier, 33 percent in 2012, 19percent in 2013 and 36percent in 2014. Based on these findings, it can be concluded that a significant number of insurers especially for 2012-2014 were not employing their inputs effectively and judiciously in producing the existing level of outputs. These results are consistent with the other finding of the study which indicates that in 2011, majority of the firms lie on or very close to the efficient frontier compared to the case in the later years.

From the second stage Tobit analysis it was found that net incurred claims, total Assets and profit after tax positively affects the overall efficiency score, There was however an inverse relationship between total commissions & other expenses, shareholders capital life fund & reserve, net earned premium and investment income & other incomes and efficiency.

In addition, the coefficient of total commissions & other expenses and efficiency, shareholders capital life fund & reserve were statistically significant. Regarding the slack analysis, it was found that in general the inputs and outputs chosen for evaluating the performance of each insurer had provided some critical and useful information about their operating performance.

Last but not least, it is critical to note that this study was characterized by a number of limitations key among these being: a) DEA limitations by the usage of negative inputs and outputs, b) limiting the determination of performance improvement potential to the use of slacks and not target analysis. On study recommendations, this study creates enough scope for future research especially the need to further investigate and examine the performance of sector to suggest areas of improvement in the industry.

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