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Technical Efficiency of Indian Life Insurance Companies-A Bootstrap DEA Approach

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Abstract

Since the Indian life insurance sector deregulated only recently, the number of players in the life insurance market is quite small and efficiency studies are based on a small set of observation. One way overcoming this small size problem is to perform bootstrap DEA. The present study, accordingly, compares the performance of the in-sample life insurance companies both on the basis of an original sample and its replications through bootstrap. The study also find out the upper and lower bounds of technical efficiency scores in the context of a 95% confidence interval.

Keywords: Life Insurance, Bootstrap DEA, Confidence Interval

Introduction

During the past one decade quite a number of new private life insurance companies have entered the Indian insurance market. Quite a number of efficiency studies have been made to evaluate the performance of the life insurance sector. However, given the small number of players in the life insurance industry, the consistency of efficiency estimates has always been open to question. The present study is perhaps the first attempt to evaluate the consistency of estimation in the context of bootstrap DEA.

Organisation

The present study is organised in to four sections and proceeds as follows. Section 1 provides an overview of the Indian life insurance industry as it stands today. Section 2 traces the evolution of non-parametric methodology for the measurement of efficiency and the use of bootstrap. Section 3 discusses the results. Section 4 concludes.

Section 1: Indian life Insurance Market-An Overview

Public sector giant Life Insurance Corporation of India had a monopoly control over the Indian life insurance market for a period of 43 years (1956-1999) which ended with the deregulation of entry in 1999. Between 2000-01 and 2011-12 the total number of life insurance companies operating in India increased from one to 24. As per the information provided by Swiss Re, India ranks 10th in terms of life insurance business out of a total of 156 countries.

The level of development of the life insurance sector in a country is usually measured by two indicators: insurance density and insurance penetration. Insurance density is computed as the ratio of premium to population i.e. per capita premium. On the other hand, insurance penetration is calculated as the percentage of insurance premium to GDP. Table 1 provides the trend observed in respect of insurance density (measured in US dollars) and insurance penetration (in percentage terms) in the Indian life insurance market for the period 2006 to 2011.

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Table 1: Trends in Life Insurance Density and Penetration (2006-2011)

Year	2006	2007	2008	2009	2010	2011
Life insurance Density	33.2	40.4	41.2	47.7	55.7	49
Penetration (%)	4.1	4	4	4.6	4.4	3.4

Source: Calculated

In the recent past, the Indian life insurance industry is going through a crisis. Thus the (inflation adjusted) real growth in premium was a negative 8.5 per cent in India for 2011-12 while the same figure for the global insurance market was -2.7 per cent. During 2010-11 and 2011-12, the sale of life insurance policies dropped relative to the previous year. Moreover, between 2010 and 2012, the total number of offices of the life insurance companies operating in India has been reduced from 12018 to 11167.

Section 2: Comparison of Performance: The Methodological Issues

Benchmarking of Productive Systems

In the context of a multi-input multi-output production system, Shephard's (1953, 1970) distance function provided a functional characterisation of the production technology. The input set of the production technology is characterised by the input distance function which gives the maximum amount by which the producer's input vector can be radially contracted. The output set, on the other hand, is characterised by the output distance function which gives the minimum amount by which the producer's output vector can be deflated and yet remain feasible for a given input vector.

Farrell (1957) laid the foundation for new approaches to efficiency and productivity studies at the micro level, providing invaluable insights on two issues: defining efficiency and productivity, and the calculation of the benchmark technology and the efficiency measures. The fundamental contribution of Farrell included the following:

(a) introduction of efficiency measures based on radial uniform contractions or expansions from inefficient observations to the frontier,

(b) specification of the production frontier as the most pessimistic piecewise linear envelopment of the data,

(c) construction of the frontier through solution of the systems of linear equations,

Farrell's definitions of efficiency had close connections with the concepts of distance function since the reciprocal of the input distance function can be considered as the radial measure of input oriented technical efficiency whereas the radial measure of output oriented technical efficiency coincides with the output distance function .

In their 1978 seminal paper, Charnes, Cooper and Rhodes (1978) provided a generalization of Farrell's Single input single output technical efficiency measure to the multiple output- multiple input case and their contribution resulted in the genesis of Data Envelopment Analysis (DEA). The methodology originally developed by Charnes, Cooper and Rhodes (1978) later further extended by Banker, Charnes and Cooper (1984). DEA enables the construction of a production frontier in the context of a multiple input-output framework with minimal prior assumption on input-output relationship.

The DEA approach constructs the efficiency frontier of productive units out of piecewise linear stretches thereby forming a convex production possibility set. In DEA frontier, efficient observations are those for which no other decision making unit or linear combination of units has as much or more of every output (given inputs) or as little or less of every input (given outputs). It envelops data sets and therefore makes no room for noise.

Once DEA identifies the efficient frontier, the performance of inefficient DMUs is improved by either increasing the current output levels or decreasing the current input levels. In the presence of undesirable outputs, however, such exercise is likely to give erroneous results. This is because, in such cases undesirable/bad outputs are to be decreased while good outputs are to be increased. The problem with the standard DEA model is that decreases in outputs are not allowed and only inputs are allowed to decrease. (Similarly, increases in inputs are not allowed and only outputs are allowed to increase.)

The BCC Model for Data Envelopment Analysis

The Banker-Charnes-Cooper (1984) model introduced performance benchmarking of productive entities based on local technology. In order to provide an extremely brief review of the model, let us consider a productive firm which produces a scalar output Y from a bundle of k inputs $x=(x_1, x_2, \dots, x_k)$.Let (x^i, y^i) be the observed input-out bundle of firm i (i=1, 2, …,n). The technology used by the firm is defined by the production possibility set.

$$Ps = \{(x, y) : y \text{ can be produced from } x\}$$

An input-output combination (x^0, y^0) is feasible if and only if $(x^0, y^0) \in Ps$

We assume the firm to be input minimiser given the level of output(s). The firm's optimization exercise can be written as:

Min θ

Subject to: $\theta x^0 \geq X\lambda$, $y^0 \leq Y\lambda$, ,$e\lambda=1$,$\lambda\geq0$

If we write the production function as: $Y=f(X) \rightarrow X=f^{-1}(Y)$. Let X* represent the miniimum input corresponding to a given level of output (say Y_f). In the presence of technical inefficiency $X^0 \leq X^*$ where X^* represents optimal input. Technical efficiency of the firm is Optimal input usage / Actual input usage = $X^* / X^0 = 1/\theta$

A characteristic feature of the BCC envelopment model is that the technical efficiency varies between 0 and 1. This is because the data set which is used to evaluate the observed firm includes the firm's data also.

Statistical Properties of DEA Estimators

The DEA approach to the estimation of technical efficiency was generally regarded as a mathematical programming based evaluation technique without any statistical foundation or justification leading to scepticism about the technique. Banker (1993), however, provided a formal statistical foundation for DEA. He showed that DEA estimators of the best practice monotone increasing and concave production function would be maximum likelihood estimators if the deviation of actual output from the efficient output is regarded as a stochastic variable with a monotone decreasing probability density function. For a finite sample size, the best practice frontier estimator would lie below the theoretical frontier. However, for large samples, the bias approaches zero. He further showed that The DEA estimators exhibit the desirable asymptotic property of consistency, and the asymptotic distribution of the DEA estimators of inefficiency deviations is identical to the true distribution of these deviations.

In practical application of DEA, statistical estimators of the frontier are obtained from finite samples. Consequently, the corresponding efficiency estimates are sensitive to the sampling variations of the obtained frontier. Korostelev et al. (1995a, 1995b) have shown that DEA estimators satisfy consistency property under very weak general conditions. However, the obtained rates of convergence are very slow.

Bootstrap DEA Estimators

Efron (1979) introduced the concept of bootstrap which involves resampling from an original sample of data through computer-based simulations to obtain the sampling properties of random variables. The starting point of any bootstrap procedure is a sample of observed data $X = \{x_1, x_2, \dots, x_n\}$ drawn randomly from some population with an unknown probability distribution f . The premise of the bootstrap method is that the random sample actually drawn "mimics" its parent population.

The sample statistic $\hat{\theta} = \theta(X)$ computed from this state of observed values is merely an estimate of the corresponding population parameter $\theta = \theta(f)$. Since the researcher has access to only one sample rather than multiple samples drawn from the same population, it is not possible to get sampling distribution of the statistic. Under the circumstances, if one draws a random sample with replacement from the observed values in the original sample, it can be treated like a sample drawn from the underlying population.

The bootstrap method suggested by Efron (1979) involves drawing of sample (with replacement) directly from the observed data and is known as naive bootstrap. In this case the bootstrap sample is effectively drawn from a discrete population which fails to recognise the fact that the underlying population density function f is continuous. Simar and Wilson (1998) suggested that the problem could be overcome by resorting to smoothed bootstrap which involves resampling via a fitted model. The smoothed bootstrap methodology involves the use of Kernel estimators as weight functions. If we write the naive bootstrap sample as $X_{nbs} = \{x_1^*, x_2^*, \dots\dots, x_n^*\}$ and the smoothed bootstrap sample as $X_{sbs} = \{x_1^{**}, x_2^{**}, \dots\dots, x_n^{**}\}$ then the elements of the two are related to each other in the following manner: $x_i^{**}=x_i^{*}+h$□ ~f, where h is the smoothing parameter for the density function while x_i^* and x_i^{**} represent the ith elements of the naive and smoothed bootstrap samples.

In case of bootstrapping, every time when we replicate the bootstrap sample, we get a different sample X**, we will also get a different estimate of $\theta^* = \theta(X^{**})$. Thus, we need to select a large number of bootstrap samples, B, in order to extract as many combinations of x_j (j = 1, 2, . . . , n) as possible. The steps followed in bootstrapping are briefly as follows:

(a) Compute the technical efficiency θ from the observed sample X.

(b) Select r^{th} (r = 1, 2, . . . ,B) independent bootstrap sample θ^*_r, which consists of n data values drawn with replacement from the observed sample θ. From this, compute the naïve bootstrap .

(c) Compute the smoothed bootstrap statistic $\theta_{sb} = \theta(X^{**}_{sb})$ from the rth naïve bootstrap sample.

(d) Construct pseudo-data from the smoothed bootstrap efficiency scores and compute technical efficiency

(e) Repeat steps (b),(c) and (d) a large number of times (say, N times).

(f) Calculate the average of the bootstrap estimate as the arithmetic mean (θ_e).

Correction of Bias

A measure of the accuracy of an estimator θ_e of the parameter θ is the bias measure $E(\hat{\theta})-\theta$. The bias-corrected estimator is: $\theta_{bc} = \hat{\theta}$-bias.In our case, we compute bias $=\theta_e - \theta$.

Thus the bias corrected estimated technical efficiency is :$\theta_{bc} = 2\hat{\theta}-\theta_e$

However, as Simar (2000) pointed out, this bias correction might create additional noise and the sample variances of the bootstrap values (σ^2_{bs}) are to be calculated.Bias correction is to be made only if : bias/$\sigma_{bs} > \sqrt{3}$.

Setting Up of Confidence Interval

By calculating the standard deviation of technical efficiency scores, we can also calculate the upper and lower bounds of technical efficiency . The upper and lower bounds are: $\bar{e}$ +mσ and $\bar{e}$ -mσ respectively (for large samples). The value of m depends on the confidence level chosen. Under Gaussian distribution and with 95% confidence interval the value of m works out to be 1.96.The lower bound of the confidence interval is 2.5% and the upper bound is 97.5%.

Section 3: Framework of Present Study and Results: Approach of the Present Paper

A number of research studies have attempted to evaluate the performance of life insurance companies of various regions/countries. In the international context, the notable contributions include Yuengert (1993), Gardner and Grace (1993), Cummins and Zi(1998), Hao and Chou (2005), Tone and Sahoo (2005), Mahlberg and Url (2010) etc.

The present paper benchmarks the performance of fifteen life insurance companies which have operated in India (on a continuous basis) for the time span 2005-06 to 2010-11 using an input oriented radial DEA model supplemented by bootstrap estimates of DEA efficiency scores. The number of replications through bootstrap has been taken as 100. Choosing a higher value for replication did not affect the result.

Selection of Output and Input: The Conceptual Issues

The outputs of financial service firms are measured according to three main approaches: the asset (intermediation) approach, the user-cost approach, and the value-added approach (refer Berger and Humphrey, 1992). The asset approach treats financial service firms as pure financial intermediaries which borrow funds from their customers from which assets are created. Interest payments are paid out to cover the time value of the funds used.

The user-cost approach (Hancock, 1985). It determines whether a financial product is an input or an output by analyzing if its net contribution to the revenues of an insurance firm is positive or negative. Thus a product is considered an output, if its financial return exceeds the opportunity costs of funds or if the financial costs of a liability are lower than the opportunity costs. Otherwise, the financial product would be classified as an input. This method would require precise information on product revenues and opportunity costs which can not be obtained for the Indian life insurance firms.

The value-added approach differs from the asset approach and the user-cost approach as it considers all asset and liability categories to have some output characteristics.

Table 2 : Descriptive Statistics of Technical Efficiency of the in-Sample Life Insurance Companies (Input Oriented Model)

Particulars	2005-06	2006-07	2007-08	2008-09	2009-10	2010-11
Mean Technical Efficiency	0.7404	0.5114	0.5581	0.5078	0.5862	0.6906
Standard Deviation	0.2868	0.2514	0.2454	0.2519	0.3519	0.2137

Source: Calculated.

Table 3 : Descriptive Statistics of Bootstrap Technical Efficiency of the in-Sample Life Insurance Companies (Input Oriented Model)

Particulars	2005-06	2006-07	2007-08	2008-09	2009-10	2010-11
Mean Technical Efficiency	0.7653	0.6420	0.6442	0.6361	0.6316	0.7111
Standard Deviation	0.3019	0.2429	0.2610	0.2800	0.3456	0.2159
Bandwidth (h) for Simar-Wilson bootstrap method	0.0043	0.0033	0.0027	0.0038	0.0053	0.0032
Mean Bias	0.0292	0.1336	0.0641	0.0589	0.1169	0.0194
Mean Bias/Sigma	0.1277	0.2500	0.2862	0.2518	0.3950	0.0928

Source: Calculated.

Those categories which have substantial value added, are then used as the important outputs. The remaining categories are treated as rather unimportant outputs, intermediate products, or inputs. An important advantage compared to the user-cost approach consists in the fact that the value-added approach uses operating cost data rather than determining the costs implicitly or using opportunity costs. The value added approach is considered to be the most appropriate method to measuring output of financial firms and is widely used in recent insurance studies.

The present paper follows a hybrid path and considers one input (Total Expenses=operating expenses and commissions) and two outputs (Sum Assured and Investment) for the estimation of technical efficiency.

Data Source

Data relating to the inputs and outputs used in the study have been collected from IRDA website. The data so collected have been appropriately deflated to make performances comparable over time.

Descriptive Statistics of Technical Efficiency

Tables 2 and 3 report the descriptive statistics of normal and bootstrap technical efficiency scores (and standard deviations) for the in sample life insurance companies. Table 3 also report the bandwidth used for smoothing purposes in the Simar-Wilson method.

Insurance Company wise Technical Efficiency Scores:

Tables 4 and 5 provide the insurance company wise technical efficiency using the original sample and the bootstrap respectively. The upper and lower bounds of technical efficiency scores based on bias corrected estimates are provided in appendix tables A 2 through A7.

Section 4: Concluding Observations

Since the insurance sector in India opened up for competition only recently, the efficiency studies relating to Indian life insurance industry are based on a small set of observations. In view of this, the present study attempted to compare the non-stochastic DEA estimates with bootstrap estimates for a successive period of six years. Table 6 presents the insurer wise mean (over the observed years) technical efficiency scores under the original DEA and the bootstrap estimates.

The basic need for having a bootstrap replication of DEA estimates arises from the problem of getting biased estimation of technical efficiency under the non-stochastic framework. However, in the present study, bias correction is required for only one insurer (ING Vysya)

Table 4: Insurer Wise Input Oriented Technical Efficiency

Insurer	*2005-06*	*2006-07*	*2007-08*	*2008-09*	*2009-10*	*2010-11*
Aviva	0.3768	0.2564	0.2699	0.2800	1	0.5949
Bajaj Allianz	0.6482	0.261	0.5005	0.6436	0.6236	1
Birla Sunlife	1	0.4205	0.5711	0.5022	0.4029	0.8895
HDFC Standard Life	0.9267	0.5346	0.4446	0.3104	0.4749	0.6141
ICICI Prudential	1	0.5734	0.4896	0.4475	0.8752	0.7232
ING Vysya	0.3505	0.2806	0.3378	0.3454	0.2555	0.3984
Kotak Life Insurance	1	0.4324	0.4667	0.4122	0.2887	0.7211
LIC	1	1	1	1	1	1
Max New York Life	0.9834	0.4775	0.4872	0.4011	0.2274	0.5394
Met Life	0.4654	0.3191	0.3967	0.3771	0.2362	0.783
Reliance	0.1807	0.3039	0.3394	0.1594	0.2596	0.3272
SBI Life	0.6773	1	1	1	1	0.9638
Sahara	0.8809	0.8444	0.9854	0.6831	1	0.6662
Shri Ram Life	1	0.5681	0.663	0.7198	1	0.5017
TATA AIA	0.616	0.3996	0.4196	0.3357	0.1497	0.5573

Source: Calculated.

Table 5: Insurer Wise Input Oriented Technical Efficiency-Bootstrap

Insurer	*2005-06*	*2006-07*	*2007-08*	*2008-09*	*2009-10*	*2010-11*
Aviva	0.7853	0.6565	0.6229	0.5724	0.6955	0.6854
Bajaj Allianz	0.7585	0.6445	0.6235	0.5773	0.7461	0.737
Birla Sunlife	0.7435	0.6684	0.6303	0.589	0.7278	0.7068
HDFC Standard Life	0.7419	0.6113	0.5924	0.5448	0.6687	0.6936
ICICI Prudential	0.8105	0.6414	0.6122	0.5416	0.7146	0.7316
ING Vysya	0.8256	0.6379	0.6154	0.5679	0.7382	0.7409
Kotak Life Insurance	0.7783	0.6679	0.6546	0.607	0.6871	0.6905
LIC	0.7125	0.6611	0.6619	0.6022	0.6671	0.677
Max New York Life	0.805	0.6231	0.6036	0.5404	0.6963	0.699
Met Life	0.7792	0.6748	0.64	0.5796	0.7068	0.7153
Reliance	0.7327	0.616	0.5982	0.5197	0.6722	0.7008
SBI Life	0.7498	0.6599	0.6284	0.5678	0.7011	0.7117
Sahara	0.8083	0.6721	0.6454	0.569	0.7249	0.7034
Shri Ram Life	0.7329	0.609	0.5885	0.5708	0.7006	0.6731
TATA AIA	0.7805	0.6317	0.6164	0.551	0.6999	0.7045

Source: Calculated.

for the year 2005-06 (please see table A1). That is to say, bias correction is required only for one out of 90 observations. This is clearly indicative of the robustness of DEA estimates of technical efficiency.

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Table A1: Insurer Wise Mean DEA and Bootstrap DEA Estimates of Technical Efficiency

Insurer	*Mean DEA Estimate*	*Mean Bootstrap DEA Estimate*
Aviva	0.4630	0.6697
Bajaj Allianz	0.6128	0.6812
Birla Sunlife	0.6310	0.6776
HDFC Standard Life	0.5509	0.6421
ICICI Prudential	0.6848	0.6753
ING Vysya	0.3280	0.6877
Kotak Life Insurance	0.5535	0.6809
LIC	1.0000	0.6636
Max New York Life	0.5193	0.6612
Met Life	0.4296	0.6826
Reliance	0.2617	0.6399
SBI Life	0.9402	0.6698
Sahara	0.8433	0.6872
Shri Ram Life	0.7421	0.6458
TATA AIA	0.4130	0.6640

Source: Calculated.

Table A2 : Company Wise Technical Efficiency with Confidence Limits (2005-06)

Company	*Bias Corrected Technical Efficiency*	*Estimated Standard Deviation*	*Confidence Limits*	
			Lower (2.5%)	*Upper (97.5%)*
Aviva	0.3768	0.2629	0	0.892
Bajaj Allianz	0.6482	0.2587	0.1411	1
Birla Sunlife	1	0.2682	0.4743	1
HDFC Standard Life	0.9267	0.2752	0.3874	1
ICICI Prudential	1	0.2459	0.5181	1
ING Vysya	-0.1246	0.2354	0	0.7982
Kotak Life Insurance	1	0.2642	0.4822	1
LIC	1	0.2852	0.441	1
Max New York Life	0.9834	0.2554	0.4828	1
Met Life	0.4654	0.2611	0	0.9771
Reliance	0.1807	0.2814	0	0.7323
SBI Life	0.6773	0.2606	0.1666	1
Sahara	0.8809	0.2672	0.3572	1
Shri Ram Life	1	0.292	0.4277	1
TATA AIA	0.616	0.2716	0.0836	1

Source: Calculated.

Table A3 : Company wise Technical Efficiency with Confidence Limits (2006-07)

Company	*Bias Corrected Technical Efficiency*	*Estimated Standard Deviation*	*Confidence Limits*	
			Lower (2.5%)	*Upper (97.5%)*
Aviva	0.2564	0.2416	0	0.7299
Bajaj Allianz	0.261	0.2496	0	0.7503
Birla Sunlife	0.4205	0.2481	0	0.9068

Company	Bias Corrected Technical Efficiency	Estimated Standard Deviation	Confidence Limits	
			Lower (2.5%)	Upper (97.5%)
HDFC Standard Life	0.5346	0.2337	0.0766	0.9925
ICICI Prudential	0.5734	0.2295	0.1236	1
ING Vysya	0.2806	0.2418	0	0.7546
Kotak Life Insurance	0.4324	0.2494	0	0.9213
LIC	1	0.2569	0.4965	1
Max New York Life	0.4775	0.2611	0	0.9893
Met Life	0.3191	0.264	0	0.8366
Reliance	0.3039	0.2435	0	0.7812
SBI Life	1	0.2332	0.5429	1
Sahara	0.8444	0.2422	0.3697	1
Shri Ram Life	0.5681	0.2528	0.0725	1
TATA AIA	0.3996	0.2524	0	0.8943

Source: Calculated.

Table A4 : Company wise Technical Efficiency with Confidence Limits (2007-08)

Company	Bias Corrected Technical Efficiency	Estimated Standard Deviation	Confidence Limits	
			Lower (2.5%)	Upper (97.5%)
Aviva	0.2699	0.2303	0	0.7213
Bajaj Allianz	0.5005	0.2273	0.0551	0.9459
Birla Sunlife	0.5711	0.2459	0.0892	1
HDFC Standard Life	0.4446	0.2145	0.0242	0.8649
ICICI Prudential	0.4896	0.2223	0.0539	0.9253
ING Vysya	0.3378	0.2163	0	0.7618
Kotak Life Insurance	0.4667	0.2462	0	0.9492
LIC	1	0.2464	0.517	1
Max New York Life	0.4872	0.2344	0.0279	0.9465
Met Life	0.3967	0.2587	0	0.9037
Reliance	0.3394	0.2266	0	0.7834
SBI Life	1	0.2277	0.5538	1
Sahara	0.9854	0.2496	0.4961	1
Shri Ram Life	0.663	0.2293	0.2136	1
TATA AIA	0.4196	0.245	0	0.8998

Source: Calculated.

Table A5 : Company wise Technical Efficiency with Confidence Limits (2008-09)

Company	Bias Corrected Efficiency	Estimated Standard Deviation	Confidence Limits	
			Lower (2.5%)	Upper (97.5%)
Aviva	0.28	0.2246	0	0.7202
Bajaj Allianz	0.6436	0.2476	0.1584	1
Birla Sunlife	0.5022	0.2539	0.0047	0.9998
HDFC Standard Life	0.3104	0.2289	0	0.7589
ICICI Prudential	0.4475	0.2457	0	0.929

Company	*Bias Corrected Efficiency*	*Estimated Standard Deviation*	*Confidence Limits*	
			Lower (2.5%)	*Upper (97.5%)*
ING Vysya	0.3454	0.2342	0	0.8044
Kotak Life Insurance	0.4122	0.2693	0	0.9399
LIC	1	0.2593	0.4917	1
Max New York Life	0.4011	0.2564	0	0.9037
Met Life	0.3771	0.2759	0	0.9178
Reliance	0.1594	0.2416	0	0.6328
SBI Life	1	0.2496	0.5107	1
Sahara	0.6831	0.2445	0.204	1
Shri Ram Life	0.7198	0.253	0.2241	1
TATA AIA	0.3357	0.2464	0	0.8186

Source: Calculated.

Table A6 : Company wise Technical Efficiency with Confidence Limits (2009-10)

Company	*Bias Corrected Efficiency*	*Estimated Standard Deviation*	*Confidence Limits*	
			Lower (2.5%)	*Upper (97.5%)*
Aviva	1	0.2982	0.4155	1
Bajaj Allianz	0.6236	0.3142	0.0078	1
Birla Sunlife	0.4029	0.2888	0	0.9689
HDFC Standard Life	0.4749	0.3098	0	1
ICICI Prudential	0.8752	0.2987	0.2897	1
ING Vysya	0.2555	0.2865	0	0.8169
Kotak Life Insurance	0.2887	0.3151	0	0.9062
LIC	1	0.3198	0.3732	1
Max New York Life	0.2274	0.3058	0	0.8266
Met Life	0.2362	0.3078	0	0.8395
Reliance	0.2596	0.3061	0	0.8595
SBI Life	1	0.3134	0.3857	1
Sahara	1	0.3014	0.4093	1
Shri Ram Life	1	0.3102	0.392	1
TATA AIA	0.1497	0.2963	0	0.7304

Source: Calculated.

Table A6 : Company wise Technical Efficiency with Confidence Limits (2010-11)

Company	*Bias Corrected Efficiency*	*Estimated Standard Deviation*	*Confidence Limits*	
			Lower (2.5%)	*Upper (97.5%)*
Aviva	0.5949	0.2058	0.1916	0.9982
Bajaj Allianz	1	0.1846	0.6383	1
Birla Sunlife	0.8895	0.2111	0.4757	1
HDFC Standard Life	0.6141	0.219	0.1847	1
ICICI Prudential	0.7232	0.1828	0.3649	1
ING Vysya	0.3984	0.2	0.0065	0.7904
Kotak Life Insurance	0.7211	0.1979	0.3331	1
LIC	1	0.215	0.5786	1

Company	Bias Corrected Efficiency	Estimated Standard Deviation	Confidence Limits	
			Lower (2.5%)	Upper (97.5%)
Max New York Life	0.5394	0.1939	0.1593	0.9194
Met Life	0.783	0.2001	0.3909	1
Reliance	0.3272	0.2109	0	0.7406
SBI Life	0.9638	0.2082	0.5557	1
Sahara	0.6662	0.1941	0.2857	1
Shri Ram Life	0.5017	0.2017	0.1063	0.897
TATA AIA	0.5573	0.2131	0.1396	0.975

Source: Calculated.