NETWORK DEA EFFICIENCY OF INDIAN NON-LIFE INSURANCE COMPANIES

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ABSTRACT

In the recent past, several research studies compared the performance of Indian non-life insurance companies in terms of efficiency and productivity. However, in all such efficiency studies, the non-life insurance companies have been considered as having black box production systems. The present study seeks to contribute to the existing efficiency literature by estimating non-life insurer performance in terms of network DEA models which enable a researcher to estimate efficiency at various sub-stages in addition to overall efficiency. Further, the study explores the impact of return on equity and solvency ratio on the efficiency performance of the in-sample insurance companies.

Keywords: Indian Non-Life Insurance Companies, Network DEA Models, Equity and Solvency Ratio, Efficiency Performance

INTRODUCTION

In India, the non-life insurance companies sell insurance policies to protect individuals and business from unforeseen losses of property, expenses related to health ailments and various kinds of liabilities. The relative insurance market, however, had only public sector players for more than quarter of a century. In 1973, the industry came under the public sector because 107 private non-life insurance companies were merged to form four non-life insurance companies and one reinsurance company. Following the deregulation of the Indian non-life insurance market in 1999, private sector operators started entering the market from the next year (2000-01). In 2015-16, 22 diversified non-life insurers existed in Indian non-life insurance market.

Compared to the pre-liberalisation phase, Indian non-life insurance industry experienced rapid growth in the post-liberalisation period. Between 2000 and 2015, 18 diversified private sector non-life insurance companies entered the Indian market. Because of the entry of the new general insurance companies, the market share of the public sector general insurance companies has come down to 55% by 2015-16. The industry experienced robust growth during the post reform phase. This is reflected in the insurance density and insurance penetration for the industry. For instance, non-life insurance density in India (equivalent to the ratio of premium in USD to total population) went up from 3.0 to 12.0 between end-March 2002 and end-March 2015. During the same period, non-life insurance penetration (measured as a ratio of premium to GDP) increased from 0.67 to 0.70. The table 1 provides a brief overview of the operating particulars of the non-life insurance industry for 2013-14 to 2015-16.

Table 1: Operating Parameters of the Indian Non-life Insurance Sector

Particulars	2013-14	2014-15	2015-16
Gross Direct Premium (Rs Million)	775538	846858	963794
Share of Public Sector Non -Life Insurer in Gross Premium (%)	54.67	50.25	49.49
Number of New Policies Issued (In Million)	102.45	118.28	122.08
Paid Up Capital (Rs Million)	68260	76220	83160
Number of offices	9,872	10,407	10,807
Incurred claims ratio	81.98	81.70	85.05
Total investments (Rs Million)	13,98094	16,07143	1748182
Insurance Penetration	0.7	0.7	0.7
Insurance Density	11	12	12

Source: IRDA Annual Report 2013-14,2014-15 and 2015-16

During the past one decade, several research studies compared the performance of Indian non-life insurance companies in terms of efficiency and productivity. However, in all such efficiency studies, the non-life insurance companies were assumed to have black box production systems. Thus, the extant Indian efficiency literature did not consider the internal sub-processes. The present study seeks to contribute to the existing literature by estimating insurer performance in terms of two network DEA models. This enables a researcher to estimate efficiency at various sub-stages in addition to overall efficiency. Further, the study explores the impact of ownership, time, incurred claims ratio reciprocal and solvency ratio on the efficiency performance of the in-sample insurance companies.

LITERATURE REVIEW

One of the earliest studies was by Toivanen (1997) which examined the economies of scale and scope in the Finnish non-life insurance industry using data set for the period 1989-91. For analytical purpose the production process of the non-life companies is decomposed in to cost and portfolio management functions. Empirical evidence relative to the Finnish non-life insurance market suggested that the creation of a branch network is important for gaining market power or informational advantages. The study confirmed the presence of diseconomies of scale at the firm level, economies of scale at the branch level and economies of scope on production.

Fukuyama & Weber (2001) examined efficiency and productivity growth of Japanese non-life insurance companies for the period 1983-1994. The paper by Farrell, Russell & Zieschang estimated the measures of output oriented technical efficiency and constructed Malmquist index of productivity growth based on these measures. The Malmquist index was decomposed in to indices of efficiency and technological change. The results from the study showed that between 1983-90 productivity improved significantly and it was mainly contributed by technological change. In the next three years the collapsed bubble economy resulted in the stagnation of technological change. However, by 1993-94, there was again an upturn in technological change.

Choi & Weiss (2005) examined the linkage between firm performance, market structure and efficiency in property-liability insurers during 1992-1998 in terms of a stochastic frontier analysis. The study estimated cost and revenue efficiency. The study tested the validity of three specific hypotheses: traditional structure-conduct-performance, relative market power, and efficient structure. The results obtained by Choi and Weiss provides support for the efficient structure hypothesis which states that more efficient firms can charge lower prices than competitors, which permits them to occupy larger market shares and extract economic rents, resulting in increased concentration in the industry. Thus, regulators should be more concerned about efficiency compared to relative market power.

Zijiang (2006) used a two-stage data envelopment analysis model for estimating the performance Canadian life and health (L&H) insurance industry. He made use of two separate models (production and investment) for the computation of efficiency (first stage) with both input and output orientations. In the next stage, a dummy input with value 1 was used and the production and (inverse of) investment efficiency scores were used as outputs. This model enabled integration of the production performance and investment performance for the insurance companies. The evidence showed that the Canadian Life & Health insurance industry operated efficiently during the period under observation.

Kao & Hwang (2006) applied a two-stage DEA model to evaluate the performance of 24 non-life insurance companies of Taiwan using data for the years 2001 and 2002. The study decomposed the activity of insurance firms into two sub-processes. The outcome of the study reveals some unusual findings compared to the black box model. Particularly, none of the insurers included in the study were found to have full efficiency in both the stages.

Barros, Nektarios & Assaf (2010) applied a two-stage robust estimation framework for estimating the efficiency performance of 71 Greek life and non-life insurance companies. The study used the global technology (constant returns to scale) framework for the period 1994-2003. This was the period during which the Third Generation Insurance Directive was initiated and implemented with the objective of deregulation of the European Union insurance market. The first stage results indicated over the sample period efficiency performance exhibited significant divergence. The second stage regression results showed that competition is a major influencing factor of efficiency in the Greek insurance industry. However, the degree of competition was not enough for raising market efficiency during the period under observation.

Mahlberg & Url (2010) examined the impact of single market project of the European Commission on the efficiency and productivity change of the German insurance companies for the period 1991-2006. The study is based on an unbalanced panel of 202 insurance companies and involved the computation of technical, revenue and cost efficiency under non-increasing returns to scale. Further, Malquist productivity indices have also been calculated. The outcomes provide a mixed picture regarding the convergence of performance among the observed insurance companies.

Cummins & Xie (2013) examined efficiency, productivity and scale economies in the U.S. property-liability insurance industry. The study analysed productivity change using Malmquist indices, and estimated efficiency using data envelopment analysis.

The results indicated that most of the insurers below median size in the industry exhibit increasing returns to scale, and most of the insurers above median size exhibit decreasing returns to scale.

RESEARCH METHODOLOGY

Efficiency of a productive unit is computed by comparing actual output/input with benchmark output /input. In the frontier approach, a production/economic frontier is constructed using the observed data and the performance of a productive unit is measured in terms of its proximity to the frontier. An overwhelming proportion of the research studies uses data envelopment analysis (DEA)-a non-parametric convex frontier approach for the estimation of the frontier (and efficiency) because of several associated advantages. To be more specific, in a non-parametric framework one need not assume a specific functional form relating outputs with inputs. Further, the application of mathematical programming (as compared to the econometric approach) enables us to handle multiple outputs.

The conventional application of DEA involves measurement of efficiency of decision-making unit (DMU) without taking in to account its internal structure. Thus, the productive system of the relative DMU is taken as a black box which is assumed to deploy certain inputs to produce certain outputs. The salient feature of such application of DEA is that the internal structure of the DMU is not considered. However, the treatment of DMUs as black box productive systems can create serious difficulty in the proper identification of weaknesses within a system.

One of the earliest DEA based study which recognised the internal processes of a productive system was by Charnes *et al.*, (1986) which identified that army recruitment is a two-stage activity. The first stage involves the creation of awareness among the youth through advertisement and the second stage involves the execution of contracts. Fare & Grosskopf (1996) demonstrated how a production technology can be represented as a network and how DEA can be used to estimate efficiency. Sexton & Lewis (2003) showed how DEA can be used to model production activity involving two stages. Further, Lewis & Sexton (2004) developed a model which includes a network of Sub-DMUs. Some of the sub-DMUs consume resources produced by other Sub-DMUs and some of which produce resources consumed by other Sub-DMUs. Liang, Cook & Zhu (2008) and Chen, Cook & Zhu (2009, 2010) also investigated the static two-stage network method.

Inter alia, one finds two important and distinct approaches to the modelling of productive units in the context of network DEA: Chen-Zhu and Tone-Tsutsui models. In the Chen-Zhu model, the inputs are deployed in the initial stage which leads to the creation of intermediate output(s) and this ultimately leads to the creation of final output. Thus, it is possible to estimate efficiency both at the intermediate as well as final stage. The overall efficiency is a weighted average of the intermediate and final stage efficiencies. In the Tone-Tsutsui model, inputs can enter at various stages of production and the productive sub-systems at various stages are connected through link variables. In the present context, two network DEA models have been considered: the two-stage centralised model introduced by Chen and Zhu (2004) and the slacks-based measure model (which is essentially a Tone-Tsutsui model) introduced by Tone & Tsutsui (2009).

(i) Chen-Zhu model of network DEA

Chen & Zhu (2004) introduced a two stage DEA model to assess the indirect impact of information technology on firm performance. In the first stage, some inputs are used to produce intermediate output(s). In the second stage, the intermediate outputs are used as to produce final outputs. To understand the framework of analysis used in this type of model, let us consider a 2-stage production process in which m inputs ($x1, x2..., xm$) are used to produce a set of intermediate outputs $b1,b2...,$ bl in the first stage of production. In the second stage, $b1,b2...,$bl are used to produce final outputs $y1, y2..., yr$. *The intermediate measures*$b1, b2...,bm$ are outputs in stage 1 and are inputs in stage 2.

For having a two-stage optimisation, the following program is required:

Min w1θ1- w2θ2

subject to

For stage 1, the optimisation program is:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_1 x_{ij0}$$

$$\sum_{j=1}^{n} \lambda_j b_{ij} \geq \tilde{b}_{ij0} \quad \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0\lambda$$

In stage 2, the output of stage becomes the input, so the optimisation program is now:

$$\sum_{j=1}^{n} \mu_j b_{ij} \leq \tilde{b}_{ij0}$$

$$\sum_{j=1}^{n} \mu_j y_{ij} \leq \theta_2 y_{ij0} , \sum_{j=1}^{n} \mu_j = 1, \mu_j \geq 0$$

Here w_1 and w_2 are user specified weights reflecting the preference related to the two stages.

(ii) Tone-Tsutsui model of network DEA

Tone & Tsutsui (2009) introduced a slacks-based measure model for estimating system (overall) and process (stage) efficiencies of DMUs with network structure. The slacks-based measure model evaluates the performance of DMUs based on output and input slacks present in observed DMUs relative to the efficient frontier points. The below mentioned paragraph provides an extremely brief overview of the slacks-based measure network DEA model.

Let us consider a reference set comprising of n DMUs. Each DMU has two divisions. Let m_i and r_i be the number of inputs and outputs relative to division i. The link connecting the two divisions is denoted by (12). The observed data on inputs, outputs and link are X^i_j (j=1,2,…,n;i=1, 2) representing the inputs, Y^i_j (j=1,2,…,n;i=1, 2) representing the outputs and $L_{(12)}$.

The production possibility set $[(X^i,Y^i,L^{(12)}]$ is defined by

$x^1{}_j \geq X^1\lambda^1,\ x^2{}_j \geq X^2\lambda^2,\ y^1{}_j \geq Y^1\lambda^1,\ y^2{}_j \geq Y^2\lambda^2$

$Lj^{12}=Z^{12}\lambda^2,\ e\lambda^1=1,\ e\lambda^2=1$

DMU 0 can be repreented by the following equalities

$x^1{}_0 = X^1\lambda^1+S^{1-},\ x^2{}_0 = X^2\lambda^2+S^{2-}$

$y^1{}_0 = Y^1\lambda^1,\ y^2{}_0 = Y^2\lambda^2,\ e\lambda^1=1,\ e\lambda^2=1$-

$\lambda^1 \geq 0,\ \lambda^2 \geq 0,\ S^{1-} \geq 0,\ S^{2-} \geq 0$

Computation of technical efficiency:

We can compute the output oriented technical efficiency by solving the following linear program:

$$\theta_0 = Max\,\{w1[1+\frac{1}{r_1}(\sum_{r=1}^{r_1}\frac{S_r^1}{y_{ro}^1})] + w2[1+\frac{1}{r_2}(\sum_{r=1}^{r_2}\frac{S_r^2}{y_{ro}^2})]\}$$

Output oriented technical efficiency = $\frac{1}{\theta_0^*}$

Output oriented divisional efficiency is computed as:

$$\theta_{Di} = \frac{1}{1+\frac{1}{r_i}(\sum_{r=1}^{r_i}\frac{S_r^i}{y_{ro}^i})}$$

Where θ_{Di} is the output oriented technical efficiency of division i (i=1, 2)

The overall output-oriented efficiency is the weighted harmonic mean of the divisional scores.

(iii) Influence of contextual variable on efficiency

Assessment of the impact of contextual variables on the determination of efficiency is an important part of the study and this must do via econometric method. However, since the efficiency scores are bounded (the lower and upper bounds being 0 and 1), ordinary least square method cannot be applied without any kind of data transformation. The present study uses logarithmic transformation of efficiency scores for the estimation of second stage results.

Banker & Natarajan (2008) considered the following relationship between the inputs, outputs and the environmental variables:

$$Y = \varphi(X)e^{-Z\beta+V-U}$$

Where Y represents to the output vector, X represents the input vector, Z represents the vector of environmental variables. U is a one-sided inefficiency process and V is a two-sided noise. Taking log on both sides, we get

$$LogY - Log\varphi(X) = V - U - Z\beta$$

Thus, we can write $\theta = V - U - Z\beta$ (1)

where $\theta = LogY - Log\varphi(X)$

Equation (1) can be estimated by applying OLS.

RESULTS AND DISCUSSION

(a) Inputs, outputs and links

For estimating efficiency of non-life insurance companies, it is essential to define inputs and outputs. However, for a financial service industry like that of non-life insurance, this is not an easy proposition. Firstly, in the Indian non-life insurance industry, excepting the four public sector players, the remaining companies came in to existence only in the current millennium. Secondly, the accounting and disclosure standards are still not at par with that of the mature economies.

Proper identification of inputs and outputs in the context of non-life industry requires understanding the intermediation process correctly. In the international context, Leverty & Grace (2010) identified two competing approaches namely the *Flow Approach* and the *Value-Added Approach*.

The *Flow Approach* considers the insurance firms as financial intermediaries which collect premiums and convert them in to claims payment. The important *Flow Approach* output indicators include rate of return on investments, the ratio of liquid assets to liabilities and the probability of solvency of the insurance company. The inputs used in this approach include the current policy holder's surplus, the sum of the costs incurred for performing the underwriting and investment functions and the policyholder supplied debt capital (represented by the sum of unpaid net losses, unpaid loss adjustment expenses and unearned premium reserves).

The alternative approach i.e. the *Value-Added Approach* uses outputs related to the amount of financial services provided by the insurance firms. The important output indicators in the *Value-Added Approach* include claims expected to be paid as a result of providing insurance coverage during a period and the average real invested assets of a firm. The important input indicators include expenditure on labour and physical capital, financial equity capital and policy holder supplied debt capital.

In the present context, a flow approach to the selection of inputs and outputs has been adopted. However, unlike the conventional approach, we have considered a two-stage intermediation process. Thus, it is essential to identify inputs and outputs for the first and second stage separately. The inputs and outputs in the present study are the same for both the models (Chen-Zhu, 2004; Tone-Tsutsui, 2009). However, since the two models considered in this paper are structurally different, entry of inputs take place at different stages in the two models. In the centralised model of Chen & Zhu (2004), we consider two inputs in the beginning (reinsurance expenses and operating expenses) which are deployed to produce an intermediate output net premium income. This intermediate output serves as the input in the second stage to produce two final outputs-incremental asset and benefits paid. In the Tone-Tsutsui (2009) model, reinsurance expenses are the only input used in the first stage which produces net premium income. This serves as the link variable between the first and second stage. In the second stage, net premium income is combined with operating expenses to produce the two outputs (incremental asset and benefits paid).

Table 2: The Input-Output Framework

Model	Stage 1	Stage 1 output	Stage 2 input	Stage 2 output
Chen-Zhu Model	Reinsurance expenses, Operating expenses	Net premium income	Net premium income	Incremental Asset, Benefits paid
Tone-Tsutsui Model	Reinsurance expenses	Net premium income	Net premium income, Operating expenses	Incremental Asset, Benefits paid

Source: Author's selection

The present study is based on data collected for the period 2009-10 to 2013-14 from IRDA Annual Reports and the Handbooks of Indian Insurance Statistics for the financial years 2011-12 and 2013-14. Fifteen general insurance companies have been included in the study. The Chen-Zhu (2004) model assumes input minimisation in the first stage and output maximisation in the second stage. The Tone-Tsutsui (2009) approach is based on output maximisation.

(b) Descriptive statistics of efficiency scores

Tables 3 and 4 present the mean efficiency scores for the two stages of insurance processes corresponding to the Chen-Zhu (2004) & Tone-Tsutsui (2009) models. It is to be noted that the mean for each of the two models, the efficiency estimates computed for the various in-sample years are based on stand-alone frontiers (for each year) and thus efficiency score are not intertemporally comparable. However, the mean efficiency score gives us an idea about the extent of divergence from the frontier corresponding to the relative financial year. Figures 1 and 2 provide graphical presentations for the mean efficiency scores for the in-sample five-year period.

Table 3: Mean Overall and Stage Wise Efficiency Scores (Chen-Zhu Model)

Particulars	2009-10	2010-11	2011-12	2012-13	2013-14
Stage 1	0.9921	0.9611	0.9922	0.8982	0.9260
Stage 2	0.7315	0.7310	0.8846	0.7063	0.7206
Overall	0.8421	0.8304	0.9287	0.7320	0.7711

Source: Calculated

Figure 1: Mean overall and stage wise efficiency scores (Chen-Zhu Model)

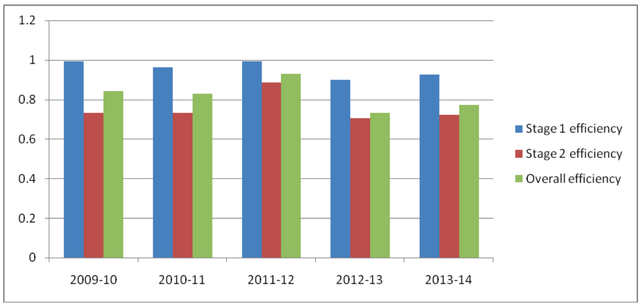
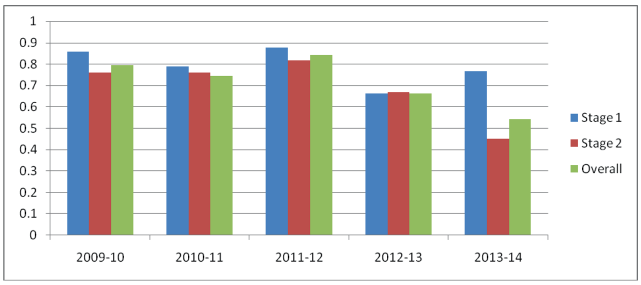


Table 4: Mean Overall and stage wise efficiency Scores (Tone-Tsutsui Model)

Particulars	2009-10	2010-11	2011-12	2012-13	2013-14
Stage 1	0.8581	0.7881	0.8776	0.663	0.7663
Stage 2	0.7597	0.7608	0.818	0.6696	0.4512
Overall	0.7965	0.7456	0.8431	0.6637	0.5422

Source: Calculated

Figure 2: Mean overall and stage wise efficiency scores (Tone-Tsutsui Model)



(c) Classification of mean efficiency performance based on ownership

In tables 5 and 6 the stage 1 efficiency scores across ownership categories are compared for the Chen-Zhu model (2004) and Tone-Tsutsui model (2009) respectively. In the Chen-Zhu model (2004), the mean efficiency score for private sector non-life insurance companies is higher than the public sector non-life companies for four out of the five in-sample years. On the other hand, in the Tone-Tsutsui model, public sector companies exhibit higher mean efficiency score than their private sector counterparts. The difference in the outcome is likely because of difference in the structures of the two model. It may be recalled that in the Chen-Zhu (2004) model the inputs enter the production process in the beginning of stage 1 while in the Tone-Tsutsui (2009) model one of the inputs (operating expenses) enter in stage 2.

Table 5: Stage 1 efficiency across ownership categories (Chen-Zhu model)

Particulars	2009-10	2010-11	2011-12	2012-13	2013-14
Public Sector non-life companies	0.9704	0.9032	0.9707	0.7585	0.9388
Private Sector non - life companies	1	0.9822	1	0.9710	0.9213
Overall	0.9921	0.9611	0.9922	0.8982	0.9260

Source: Calculated

Table 6: Stage 1 efficiency across ownership categories (Tone-Tsutsui model)

Particulars	2009-10	2010-11	2011-12	2012-13	2013-14
Public Sector non-life companies	0.9849	0.9605	0.9917	0.5796	0.9462
Private Sector non - life companies	0.8119	0.7254	0.8361	0.8925	0.7009
Overall	0.8581	0.7881	0.8776	0.6630	0.7663

Source: Calculated

However, the results available for the stage 2 efficiency across ownership categories for the Chen-Zhu (2004) and Tone-Tsutsui (2009) models are compatible with each other for the entire observation period. Tables 7 and 8 represent the comparative mean efficiency scores for the public and private sector non-life insurance companies for the Chen-Zhu (2004) and Tone-Tsutsui (2009) models respectively.

Table 7: Stage 2 efficiency across ownership categories (Chen-Zhu Model)

Particulars	2009-10	2010-11	2011-12	2012-13	2013-14
Public Sector non-life companies	0.9401	0.9383	1	0.9669	0.9529
Private Sector non - life companies	0.6556	0.6556	0.8427	0.6115	0.6361
Overall	0.7315	0.7310	0.8846	0.7063	0.7206

Source: Calculated

Table 8: Stage 2 efficiency across ownership categories (Tone-Tsutsui model)

Particulars	2009-10	2010-11	2011-12	2012-13	2013-14
Public Sector non-life companies	0.8718	0.9379	0.9054	0.9199	0.6530
Private Sector non - life companies	0.7190	0.6964	0.7862	0.5787	0.3778
Overall	0.7965	0.7456	0.8431	0.6637	0.5422

Source: Calculated

(d) Impact of contextual variables on efficiency scores

In the present study, the censored regression approach has been used for exploring the impact of contextual variables on the stage 1 and stage 2 efficiency scores. In this context, we are interested to know how efficiency is influenced by commonly used performance indicators. Thus, for both the Chen-Zhu (2004) and Tone-Tsutsui (2009) network DEA models, we have included solvency ratio and return on equity as the contextual variable. The impact of contextual variables has been assessed for both stage 1 and stage 2 efficiency scores.

Regression estimates of contextual variables on stage 1 efficiency

Tables 9 and 10 represent the fixed and random effects panel data estimates of the effect of solvency ratio and return on equity on stage 1 efficiency scores of the non-life insurance companies for the Chen-Zhu (2004) and Tone-Tsutsui (2009) models. The regression outcome relating to the first stage efficiency scores is, however, contingent on the model being used by us. Let us consider table 9 which compares the results available from the fixed effect and random effect models with the Chen-Zhu (2004) stage 1 efficiency scores. The results show that results are not statistically significant. In table 10, we have presented the regression results corresponding to the stage 1 efficiency scores obtained from the Tone-Tsutsui (2009) model. For both the fixed effects and random effects approach, the coefficients of Solvency ratio are found to be statistically significant. Note that the statistically significant variables are indicated by "***","**" and "*" according to the levels of significance (***for significance level ≥99%,** for significance level≥**97.5% and * for significance level≥**95%).

Table 9: Impact of contextual variables on stage 1 efficiency (Chen-Zhu Model)

Model	Particulars	Coefficient	Standard Error	Coefficient/ Standard Error	Probability of type 1 error
Fixed effect model	Constant	−0.04821	0.0953	−0.5061	0.6206
	Solvency ratio	0.0558	0.0933	0.5982	0.5592
	Return on equity	−0.0112	0.0560	−0.1999	0.8444
Random effect model	Constant	−0.0080	0.0956	−0.0835	0.9335
	Solvency ratio	−0.0932	0.05773	−1.614	0.1066
	Return on equity	−0.0275	0.0627	−0.4387	0.6608

Source: Calculated

Table 10: Impact of contextual variables on stage 1 efficiency (Tone-Tsutsui Model)

Model	Particulars	Coefficient	Standard Error	Coefficient/ Standard Error	Probability of type 1 error
Fixed effect model	Constant	0.5433	0.1927	−2.819	0.0136**
	Solvency ratio	0.9478	0.3451	2.803	0.0141**
	Return on equity	0.09478	0.1103	0.8594	0.4046
Random effect model	Constant	−0.5522	0.1934	−2.855	0.0043***
	Solvency ratio	0.7150	0.3294	2.170	0.0300**
	Return on equity	0.1116	0.0968	1.153	0.2491

Source: Calculated

Regression estimates of contextual variables on stage 2 efficiency

Tables 11 and 12 include the regression outcomes for stage 2 efficiency scores. Table 11 provides the results obtained from the application of fixed and random effects approach in the context of Chen-Zhu (2004) stage 2 efficiency scores. Table 12 states the results for the impact of contextual variables with stage 2 Tone-Tsutsui (2009) efficiency scores being taken as the regressand. For both the impact of the two contextual variables is statistically significant.

Table 11: Impact of contextual variables on stage 2 efficiency (Chen-Zhu): Fixed Effect Model

Model	Particulars	Coefficient	Standard Error	Coefficient/ Standard Error	Probability of type 1 error
Fixed effect model	Constant	−0.5776	0.1391	−4.153	0.0010
	Solvency ratio	0.6719	0.2281	2.946	0.0106**
	Return on equity	0.1024	0.0812	1.261	0.2280
Random effect model	Constant	−0.5641	0.1368	−4.123	<0.001
	Solvency ratio	0.5570	0.2514	2.215	0.0267**
	Return on equity	0.0999	0.0743	1.346	0.1785

Source: Calculated

Table 12: Impact of contextual variables on stage 2 efficiency (Tone-Tsutsui): Random Effect

Model	Particulars	Coefficient	Standard Error	Coefficient/ Standard Error	Probability of type 1 error
Fixed effect model	Constant	−0.9539	0.1357	−7.031	<0.0001
	Solvency ratio	1.0344	0.2773	3.730	0.0022***
	Return on equity	0.2375	0.0768	3.092	0.0080***
Random effect model	Constant	−0.8465	0.1828	−4.631	<0.0001
	Solvency ratio	0.6406	0.2958	2.166	0.0303**
	Return on equity	0.1938	0.0721	2.686	0.0072***

Source: Calculated

CONCLUSION

The present study enables us to explore efficiency scenario in Indian non-life insurance companies for the observation period for the different stages of production which was not possible in the extant efficiency literature pertaining to the Indian non-life insurance sector. The study also enables us to explore the impact of a few contextual variables on the efficiency performance of the in-sample companies.

The study, however, has several limitations. Firstly, the assumptions made in two models are a bit drastic. In the Chen-Zhu model, we have assumed that all operating expenses are incurred in the beginning while in the Tone-Tsutsui model it is assumed that the operating expenses are incurred in the second stage only. However, a part of the expenses is incurred in the first stage and the remainder is incurred in the second stage. However, this could not be accommodated in the second model because we do not have the break up information about operating expenses. Secondly, in the absence of adequate disclosures (as per international standards) only two financial indicators (return on equity and solvency ratio) could be included in the analysis for examining their influence on the efficiency scores. Thirdly, the study is limited to a five-year period only. With more disclosures and maturing of the non-life market in India, it is expected that a more comprehensive study could be undertaken in future.

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