

Mapping Efficiency Frontiers in India's Life Insurance Sector: An Integrated DEA-TOPSIS Approach

barkha Goyal

barkha.goyal@dsb.edu.in

Delhi School of Business

Research Article

Keywords: efficiency, peers, target setting, data envelopment analysis, insurance firms

Posted Date: October 14th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10956104/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Mapping Efficiency Frontiers in India's Life Insurance Sector: An Integrated DEA-TOPSIS Approach

Abstract

The purpose of this paper is to estimate the efficiency levels of 22 life insurers operating in India for the year 2022/23, while also identifying peer groups and setting performance targets for inefficient firms. To achieve this, input-oriented CCR and BCC Data Envelopment Analysis (DEA) models have been used to compute efficiency scores, and the TOPSIS approach has been applied to provide strict rankings among efficient insurers operating on the best-practice frontier. The empirical findings indicate that an average life insurer, if operating on the efficient frontier rather than at its current (virtual) location, could produce the same level of output using only 81.1 percent of its existing inputs. The results further suggest that inefficiency primarily stems from managerial incompetence rather than inappropriate scale size. The ranking analysis reveals that Reliance Nippon Life Insurance secures the top position, whereas Edelweiss Tokio Life Insurance ranks at the bottom. Moreover, the findings show that scope exists for input reduction and output augmentation across all inefficient insurers.

Keywords efficiency; peers; target setting; data envelopment analysis; insurance firms

JEL codes G22, D61

1. Introduction

The efficient insurance industry is key for the development of any nation because apart from shielding individuals or businesses against the unpredictable potential risk, this industry likewise contributes to a significant extent in achieving higher economic growth rates. Indeed, the insurance industry provides long-term capital for investment and growth of the economy (Parida and Acharya 2016) and plays an important role in maintaining the financial stability of the economy. Truly, there is a myriad of linkages between the insurance sector and macroeconomic development (Ray et al. 2020). In recent years, the life insurance segment of the Indian insurance industry witnessed a fall in the concentration and an increment in the intensity of competition. There is no doubt that in such a competitive industry, only those insurance firms can survive who utilise their resources efficiently.

In their prominent survey article, Eling and Luhnen (2010) reviewed 95 empirical studies that utilized frontier methodologies of data envelopment analysis (DEA) and stochastic frontier analysis (SFA) to compute efficiency estimates for insurance firms. In their survey, the study of Tone and Sahoo (2005) was the only study on the efficiency performance of the Indian insurance industry. A most recent survey of Kaffash et al. (2020) that reviewed and analysed 132 DEA-based studies in the insurance industry published from 1993 through July 2018 also included one more Indian study by Sinha (2017). Even though the geographical scope of these survey articles is extensive and covers profusely the studies on emerging markets like China, Taiwan, Malaysia, yet

only two studies on the Indian insurance industry are included in these profound literature reviews. Regardless of a spike in the efficiency studies for insurance firms in other emerging economies in recent years, we actually have sparse literature on the efficiency of Indian insurance firms. In addition to the aforementioned studies, some important studies in the Indian context include Dutta and Sengupta (2011), Sinha and Chatterjee (2011), Chakraborty et al. (2013), Dutta (2013), Sinha (2014, 2015), Chakraborty (2016), Chakraborty and Harper (2017), Parida and Acharya (2017), Anandaramo et al. (2018), Shetty and Basri (2020), Sen (2020), Bhatia and Mahendru (2022, 2023), Siddiqui and Shaddady (2023). A shared characteristic in the above-mentioned available studies is that these studies share the practically indistinguishable research objective of getting efficiency estimates and analysing their inter-temporal variations.

Against this backdrop, we here attempted to differ from other DEA-based studies on the Indian life insurance industry and present the inputs and outputs targets for inefficient firms along side their (in)efficiency estimates. The target values have been used for designing the strategy at a micro-level for mitigating the waste of inputs and augmentation of outputs. We look at this as a significant contribution to the extant literature regarding the efficiency of life insurers in India. Additionally, we employ the popular multi-criterion decision-making tool of TOPSIS technique for the ranking of efficient firms and getting a strict ranking of sampled insurance firms. The TOPSIS method helps us to circumvent the problem of infeasibility that the most popularly used Andersen-Peterson's (1984) super-efficiency model for ranking the efficient firms faces. Under the TOPSIS method, efficient units are ranked according to their relative distance from the worst value and proximity to the best value, whereas while the super-efficiency model provides an alternative ranking based solely on the distance from the best value. The integration of TOPSIS with DEA for deriving a strict ranking of insurance firms remains unexplored in the Indian insurance context, and addressing this gap represents a key contribution of the present study. This study focuses exclusively on life insurance firms, given that the life insurance segment contributes approximately 74 percent to the total premium income of the insurance industry. In addition, this segment accounts for roughly 90 percent of the total investment from the insurance industry. Using the dataset for 22 life insurance firms for the year 2022/23, this study primarily aims to assess their average (in)efficiency levels and to establish a strict ranking among them. Another significant goal of the present study is to provide the input and output target values for inefficient firms.

The remainder of this paper is organized as follows. Section 2 provides the relevant literature on the efficiency of insurance sector. Section 3 describes the methodological framework that has been used to obtain the empirical results. Section 4 deals with the issue of measurement of inputs and outputs. The empirical results are discussed in the section 5. The final section provides a brief conclusion and suggests the area for future research.

2. Literature review

Given the importance of insurance industry, a plethora of research efforts have been made to evaluate the efficiency of insurance firms. Several key issues (i.e., deregulation, organizational

structure, merger and acquisitions, corporate governance, competition, risk-taking, intellectual capital) have been linked with the efficiency assessment in the literature. Nevertheless, the existing literature is largely concentrated on developed economies, notably the USA and EU countries. The research efforts in emerging or developing nations, especially in India, are still in infancy. This fact is well reflected by the two prominent survey articles of Eling and Luhnen (2010) and Kaffash et al. (2020). The former survey article covers 95 studies, 70 out of them only focused on USA and European market and only one Indian (Tone and Sahoo 2005) study has been included in this survey. The main focus of this survey was on analysing the frontier efficiency methodologies and on the choice of inputs and outputs. The findings of this survey recognised DEA and SFA as the most frequently used technique in the insurance efficiency literature. In addition, they found a widespread agreement regarding the choice of inputs and outputs. They reveal most of the studies used three inputs (i.e., labour, capital and business services) to define the inputs of insurance sector and for the selection of outputs most of the studies preferred value-added approach. The recent survey article by Kaffash et al. (2020) covers only DEA based studies. The scope of this article is extensive and covers the various emerging area of research in insurance efficiency. The survey article by Kaffash et al. (2020) also included several studies on emerging markets like China, Taiwan, Malaysia, and Thailand, but included only one study on the Indian insurance industry. A list of recent studies on efficiency and productivity evaluation in the Indian life insurance industry is given in Table 1.

A study by Dutta and Sengupta (2011) explored the efficiency of Indian life insurance firms in the post-reforms period 2004-2009 and revealed that on an average overall technical efficiency has improved during the observation period but the scale efficiency has deteriorated. By applying DEA based window analysis Sinha and Chatterjee (2011) evaluated the technical efficiency of life insurers and found huge gap between the performance of LIC and private insurers. In the same row, Chakraborty et al. (2013) investigated efficiency and productivity in life insurance firms and found that life insurers have moved away from the optimal scale over the study period and the insurers which are dealing in both life and non-life insurance business performed better than the firms which are dealing only in life insurance business. Further, Dutta (2013) examined the impact of privatization on the productivity of life and non-life insurance firms by employing DEA based Malmquist approach and revealed that the total factor productivity of non-life insurers has improved while the productivity of life insurers has declined during the study time period. Using a slack-based DEA model, Sinha (2015) assessed the technical efficiency of life insurers and found the huge variations in their efficiency scores. Similarly, Chakraborty (2016) observed that management inefficiency is the main source of overall inefficiency in the Indian life insurance market during the observation period. Parida and Acharya (2017) found that Indian life insurance industry is operating at moderate level of efficiency and average productivity has increased only by one percent during the study time period. Anandaram et al. (2018) realized insurers who have concentrated on second stage output that profits are more efficient than the insurers who have more concentrated on first stage output that premium income. Shetty and Basri (2020) focused on the

efficiency of traditional individual agents and corporate agents and reveals that there is no significance difference between their efficiencies. Sen (2020) evaluated technical, cost and allocative efficiency of the Indian life insurance industry for the time span 2005-06 to 2015-16 using DEA approach. The empirical results revealed that the LIC was technical as well as cost efficient for the initial years of study but after 2009-10 it has become cost inefficient. However, private insurers were inefficient in terms of both technical as well as cost efficiency for the entire study time period. Bhatia and Mahendru (2022) found most life insurers exhibit decreasing returns to scale. At the same time, the group of leading firms has shrunk, and number of firms classified as laggards has increased. Bhatia and Mahendru (2023) observed that public insurer (LIC) outperform the group of privates' insurers. Similarly, Siddiqui and Shaddady (2023) found that LIC demonstrates higher profitability and greater cost efficiency than their private counterparts. From the table 1, we can see that all the existing studies in Indian insurance sector have relied on DEA technique for the efficiency and productivity evaluation. This fact underscores the growing importance of DEA in the insurance efficiency literature. We observed that most of the existing studies in Indian context provide only efficiency scores and their trends. There is dearth of studies which focuses on other qualitative and quantitative dimensions of DEA analysis. Perhaps, this is the first study that provides peer analysis and the inputs and outputs targets for the inefficient Indian life insurance firms for the recent year. Second, available studies relied on Anderson Peterson super efficiency DEA model (see for instance Garg and Garg 2020) to rank the efficient insurers. To best of our knowledge, none of the study has provided the strict ranking for the Indian life insurance firms using TOPSIS approach till date. Further, the current study contributes to the existing literature by assessing returns to scale in the insurance sector to systematically identify the “leaders” and “laggards”, an analysis that has not been taken in prior research. By incorporating this dimension, the study fills an important gap in the extant literature and provides deeper insights into firm-level performance dynamics within the industry.

Table 1: Selected empirical studies evaluating efficiency in the Indian life insurance sector					
Author (Year)	Period of study	Data and Sample	Estimation Method(s)	Input variables	Output variable(s)
Dutta and Sengupta (2011)	2004-2009	14 life insurers	DEA-CCR, BCC	Net benefits paid to the policyholders, operating expenses, commission paid to the agents	Net premium revenues
Sinha and Chatterjee (2011)	2003-2007	13 life insurers	DEA-Window analysis	Total expenses (commission paid + operating expenses)	Net premium income, operating income
Chakraborty et al. (2013)	2005-2009	14 life insurers	DEA-CCR, BCC and MPI	Debt capital, equity capital, operating expenses, commission expenses	Incurred benefits, income from investment
Dutta (2013)	2006-2010	15 life and 12 non-life insurers	DEA-MPI	Total investment, expenses related to business service and materials, expenses related to labour	Premium earned, income from investment

Sinha (2014)	2006-2010	15 life insurers	Slack based DEA model	Commission expenses, operating expenses	Undesirable: lapsed sum assured Desirable: sum assured
Sinha (2015)	2006-2012	15 life insurers	Dynamic slack based DEA	Operating and commission expenses	premium collected and sum assured, investment
Chakraborty (2016)	2009-2015	18 life insurers	DEA-CCR, BCC	Operating expenses, commission expenses, investment	Net premium earned, benefits paid, income on investment
Chakraborty and Harper (2017)	2008-2016	14 life and 18 non-life insurers	DEA-MPI	Equity capital, operating expenses, total investment, total assets	Income from investment, net premium income
Parida and Acharya (2017)	2002-2014	13 life insurers	DEA-CCR, BCC and MPI	Number of agents, total commission expenses, equity capital, debt capital	Net benefits paid, liquid assets to liabilities
Anandarao et al. (2018)	2013-14	17 life insurers	Two-stage network DEA	First stage inputs: operating expenses, insurance expenses. Intermediate inputs: Total premium, reinsurance premium	Final outputs: total profits other than investment profits, investment profits
Shetty and Basri (2020)	2012-2016	12 life insurers	DEA-CCR	Commission expenses, total number of agents	Total policies sold, average business premium
Sen (2020)	2006-2016	All operating insurers during the study period	DEA-technical, cost and allocative efficiencies	Number of agents, number of branches, debt capital, equity capital	Benefits paid, net premium income
<i>Contd...</i>					
Bhatia and Mahendru (2022)	2014-2018	24 life insurers	DEA-revenue efficiency	Number of agents, shareholder fund	Investments, net Premium Received
Bhatia and Mahendru (2023)	2014-2021	24 life insurers	DEA-cost, revenue, and profit efficiencies	Number of agents, shareholder fund	Investments, net Premium Received
Siddiqui and Shaddady (2023)	2017-2021	24 life insurers	DEA-cost and profit efficiencies	Debt capital, equity capital, operating expenses	Invested assets, incurred benefits plus addition to reserves
Source: Author's compilation					

3. Methodology

3.1 Measurement of technical efficiency: CCR and BCC DEA model

As discussed, the study adopts data envelopment analysis (DEA) approach to evaluate the technical efficiency of life insurers in India. DEA is a non-parametric mathematical programming approach commonly used to assess the relative efficiency of decision-making units (DMUs). The intuitive model of DEA was proposed by Charnes, Cooper and Rhodes (hereafter, CCR) in 1978 which assumes constant returns to scale. It was later generalized by Banker, Charnes and Cooper (1984) (hereafter, BCC) to accommodate variable returns to scale. DEA allows the construction of a piecewise linear segmented *efficient frontier*, with the DMUs defining the frontier is known as *best practice* firms and holds a value of one. DMUs located beneath the efficiency frontier are classified as relatively inefficient, with efficiency scores bound between 0 and 1.

The present study utilized the input-oriented CCR and BCC DEA models, as it is assumed that organizations seek to optimize inputs utilization while attaining the desired output levels. A set of liner programming problems is solved to estimate these models. Here we assumed that there are $j = 1, 2, \dots, n$ are life insurers, where each life insurer generates s outputs (symbolized by y_r , where $r = 1, 2, \dots, s$) utilizing m inputs (denoted by x_i , where $i = 1, 2, \dots, m$), then the efficiency of p^{th} DMU is estimated by solving the following linear programming problem.

$$\begin{aligned}
 (a) \quad & \min_{\theta_p, \lambda_1, \lambda_2, \dots, \lambda_n, s_i^-, s_r^+} OTE_p = \theta_p - \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \\
 & \text{subject to} \\
 (b) \quad & \sum_{j=1}^n \lambda_j x_{ij} + s_i^- = \theta_p x_{ip} \quad i = 1, 2, \dots, m \\
 (c) \quad & \sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = y_{rp} \quad r = 1, 2, \dots, s \\
 (d) \quad & s_i^-, s_r^+ \geq 0 \\
 (e) \quad & \lambda_j \geq 0, \quad j = 1, 2, \dots, n \quad (1)
 \end{aligned}$$

Where

x_{ip} = amount of input i utilized by DMU p .

y_{rp} = amount of output r generated by DMU p .

s_i^- = input slack.

s_r^+ = output slack.

λ = intensity variable.

ε = a small positive number.

The above linear programming formulation represents the envelopment form of CCR model, which yields the Farrell input-oriented measure of OTE under the CRS assumption. The OTE scores are denoted as θ_p^{CCR} . When we add one more restriction $(f) \sum_{j=1}^n \lambda_j = 1$ if VRS, then the above

model is defined as BCC model. BCC model provides the PTE scores, i.e., symbolize as θ_p^{BCC} . To obtain the optimal values of $\theta_p, \lambda_1, \lambda_2, \dots, \lambda_n, s_i^-, s_r^+$ (i.e. $\theta_p^*, \lambda_1^*, \lambda_2^*, \dots, \lambda_n^*, s_i^-, s_r^+$), both models are solved n times, considering one DMU at a time. The results of the above model can be interpreted as: if $\theta_p^{CCR} = \theta_p^{BCC} = 1$, it means insurance firm under evaluation is fully efficient, there is no other firm is more efficient. In addition, if θ_p^{CCR} (or θ_p^{BCC}) < 1 , it means insurance firm under assessment is not efficient and must either improve its output levels or reduce its input usage to achieve full efficiency. The scale efficiency (SE) scores are derived by dividing OTE by PTE, and are denoted as $\theta_p^{CCR} / \theta_p^{BCC}$.

3.2 Nature of returns-to-scale

As stated above, the scale efficiency of insurer p (i.e., denoted by μ_p^*) is determined by taking the quotient of its OTE and PTE (i.e., denoted as $\theta_p^{CCR^*} / \theta_p^{BCC^*}$). It is important to note that if $\theta_p^{BCC^*} \geq \theta_p^{CCR^*}$ then it follows $\mu_p^* \leq 1$. If $\mu_p^* = 1$, then insurer p is termed as fully scale efficient and if $\mu_p^* < 1$, then the insurer p is scale inefficient. Scale inefficiency can arise due to two possible underlying factors. First, the insurer might be experiencing increasing returns-to-scale (IRS), which suggests that it is operating at sub-optimal scale size and could improve its level of efficiency by expanding its scale of operations. Alternatively, insurer may operate at decreasing returns-to-scale (DRS) that implies that the particular insurer is operating at supra-optimal scale size and it could improve their efficiency by downsizing their scale of operations. Therefore, to identify whether an insurer operates at IRS or DRS, an additional DEA model is estimated by imposing non-increasing returns-to-scale (NIRS) and non-decreasing returns-to-scale NDRS restrictions. Appropriate modifications to the BCC model are used to achieve this, we substitute the $\sum_{j=1}^n \lambda_j = 1$ restriction with $\sum_{j=1}^n \lambda_j \leq 1$ for NIRS and $\sum_{j=1}^n \lambda_j \geq 1$ for NDRS. To estimate the technical efficiency scores under NIRS and NDRS assumptions, the following linear programming model is solved.

$$(a) \min_{\pi_p, \lambda_1, \lambda_2, \dots, \lambda_n, s_i^-, s_r^+} TE_p = \pi_p - \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right)$$

Subject to

$$(b) \sum_{j=1}^n \lambda_j x_{ij} + s_i^- = \pi_p x_{ip} \quad i = 1, 2, \dots, m$$

$$(c) \sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = y_{rp} \quad r = 1, 2, \dots, s$$

$$(d) \sum_{j=1}^n \lambda_j \leq 1 \quad \text{if NIRS}$$

$$(e) \sum_{j=1}^n \lambda_j \geq 1 \quad \text{if NDRS}$$

$$(f) s_i^-, s_r^+ \geq 0$$

$$(g) \lambda_j \geq 0 \quad j=1, 2, \dots, n \quad (2)$$

Note that if $\mu_p^* < 1$ and $\theta_p^{CCR^*} = \pi_p^*$, then SIE is caused by IRS, suggesting that the insurer is operating at a scale smaller than the optimal level. In contrast, when $\mu_p^* < 1$ and $\theta_p^{CCR^*} < \pi_p^*$ hold, SIE is due to DRS, indicating that the insurer is operating beyond the optimal scale size.

3.3 Technique for order performance similarity to ideal solution (TOPSIS)

As noted above, under the conventional DEA model, all efficient units get the efficiency score equal to one. As resultant, it becomes impossible to discriminate or rank the efficient insurers with conventional DEA model. So, in order to rank the efficient insurers, Hwang and Yoon (1981) developed a method i.e., known as TOPSIS technique. This model was further developed by Yoon (1987) and Hwang, Lai and Liu (1993). TOPSIS is a distance-based approach which provides ranks to the efficient units according to their proximity to the positive ideal solution and their distance from negative ideal solution. The positive ideal solution represents the most preferred outcome by maximising benefit criteria and minimising cost criteria, whereas the negative ideal solution represents the least preferred outcome by minimising benefit criteria and maximising the cost criteria. To illustrate the TOPSIS method, we assumed here Z_{ia} be the inputs for the matrix of priorities. Where $i = 1, 2, \dots, m$ alternatives and $a = 1, 2, \dots, n$ criteria. TOPSIS has the six-step procedure to assign the ranks to equally efficient unit.

Step1: Construct normalized decision matrix:

$$P_{ia} = \frac{Z_{ia}}{\sqrt{\sum_{i=1}^m \sum_{a=1}^n Z_{ia}^2}}$$

Step 2: Obtain weighted normalized decision matrix:

$$y_{ia} = w_i p_{ia}, \quad i = 1, 2, \dots, m; \quad a = 1, 2, \dots, n$$

Step 3: Define the positive ideal solution (maximum value) and negative ideal solution (minimum value):

$$R^+ = \{y_1^+, \dots, y_n^+\}, \text{ where } y_a^+ = \begin{cases} \max(y_{ia}) & \text{if } a \in A; \\ \min(y_{ia}) & \text{if } a \in A' \end{cases}$$

$$R^- = \{y_1^-, \dots, y_n^-\}, \text{ where } y_a^- = \begin{cases} \min(y_{ia}) & \text{if } a \in A; \\ \max(y_{ia}) & \text{if } a \in A' \end{cases}$$

Step 4: Calculate the distance from positive and negative ideal solution:

$$S_i^+ = \sqrt{\sum_{a=1}^n (y_a^+ - y_{ia})^2}$$

$$S_i^- = \sqrt{\sum_{a=1}^n (y_a^- - y_{ia})^2}$$

Step 5: Compute the closeness coefficient for each alternative:

$$C_i^+ = \frac{S_i^-}{S_i^- + S_i^+}, \quad 0 < C_i^+ < 1$$

Step 6: Assign ranks based on their coefficient values, with a higher coefficient implying a higher rank or vice versa.

4. Data and variables

Like other financial institutions, selecting appropriate input and output variables to measure insurer efficiency is particularly challenging because several inputs are not directly observable and certain outputs are intangible. The literature on insurance efficiency spells three different approaches for the selection of variables, including i) asset approach, also called *intermediation approach*, ii) user-cost approach and iii) value-added approach, also called *production approach* (Eling and Luhnen 2010). Under the intermediation approach, an insurance company is considered as a pure financial intermediary, which manages a pool of assets, collects the funds from the policyholders, pays out claims, and invests the remaining funds in capital market (Brockett et al. 1998). This approach, however, avoids the risk-pooling and risk-bearing services of life insurers. The ‘user-cost’ approach defines the financial product either as an input or output based on the net contribution to revenue of the life insurers (Hancock 1985). If the financial return exceeds their opportunity cost of funds then a financial product is considered

as an input else as an output. The third approach called ‘value-added’ differs in the sense that as it considers the service as an output only if it contributes a substantial value addition based on its operating cost allocation. (Berger et al. 2000). In the survey articles of Eling and Luhnén (2010) and Kaffash et al. (2020) noted that the value-added approach has been extensively adopted for the specification of input-output variables for insurance efficiency measurement.

Therefore, following Diacon et al. (2002); Hao and Chou (2005), and Huang and Eling (2012), we adopted the value-added approach to determine the output vector. The choice of this approach is appropriate since it assumes that firm provides a full range of services including, i.e., risk-pooling/ risk-bearing, ‘real’ financial and intermediation services (Eling and Luhnén 2010). To capture the risk-pooling/ risk-bearing function, the literature suggests the use of either incurred losses or net premium earned as a proxy. Traditionally, the studies by Yuengert (1993) and Cummins and Zi (1998) suggest the use of real losses as an appropriate proxy for risk-pooling/risk-bearing services. However, Study by Jarraya and Bouri (2013), Reyna and Fuentes (2018) argued that claims incurred (or losses incurred) is an undesirable output for an insurance firm and insurer look forward to minimizing the production of this output. Therefore, net premium earned is used in this study as a proxy for the risk-pooling and risk-bearing service. For the intermediation role, income from investment activities is taken as the proxy (see, for instance, Boonyasai et al. 2002; Diacon et al. 2002; Cummins and Xie 2008; Amri et al. 2012, among others). Thus, the output vector includes net premium earned and income from investment as two output variables. The selection of both the output variables is associated with the third function of insurers, i.e., financial services; therefore, no separate proxy for financial services has taken.

In the input vector, the operating expenses and net commission expenses are taken as the proxy for labour and business services because most of the management expenses in the insurance industry occurred due to remuneration to employees and commission to agents. Further, Equity capital taken as the proxy for capital input as it captures the risk-pooling function by providing assurance to the policyholders as company holds buffer capital to pay claims if losses are larger than expected (see Huang and Eling, 2012). Therefore, this study uses three inputs- equity capital, operating expenses and commission expenses for the efficiency measurement of insurers. The explanation of three input and two output variables utilized in the present study is given in Table 2.

Table 2: Explanation of input and output variables		
Variables	Description of the variable	Unit of measurement
Inputs		
Equity capital (x_1)	Share capital + reserve and surplus + credit/debit fair value change account + share application money pending allotment	Lacs
Net Commission (x_2)	Commission paid + commission on re-insurance accepted - commission on re-insurance ceded	Lacs
Operating expenses (x_3)	Employees' remuneration + travelling expenses + rent, rates and taxes + Depreciation + others	Lacs
Outputs		
Net premium earned (y_1)	Total premium – reinsurance ceded + reinsurance accepted	Lacs
Income from Investment (y_2)	Income from investment on policyholders' investment + Income from investment on shareholders' investment	Lacs
Source: Author's compilation		

Data for the selected input and output variables are collected from the 'Handbook of Indian Insurance Statistics', published by the Insurance Regulatory and Development Authority of India (IRDAI). The study exclusively focuses on the year 2022/23. The efficiency results using a data envelopment analysis approach are influenced by the sample size; therefore, the adequacy of sample size is checked using the rule of thumb suggested by Cooper et al. (2007).

In our study, the number of life insurance firms are i) greater than the product of the number of inputs and number of outputs, i.e., $(n > (x \times y) = 22 > (3 \times 2))$, and ii) greater than equal to the three times sum of number of inputs and number of outputs, i.e., $(n \geq 3 \times (x + y) = 22 \geq 3 \times (3 + 2))$. Thus, the sample size in this present study is adequate and sufficiently large to ensure the required discriminatory power.

5. Empirical results

5.1 Discussion on Overall technical efficiency Scores

This section discusses the technical, pure, and scale efficiency scores estimated using the CCR and BCC models. Notably, input-oriented efficiency measures examine the extent to which input quantities can be proportionally reduced while maintaining the same level of output. Table 3 presents efficiency scores of 22 life insurance firms operating in India, along with the nature of returns to scale and rankings. The results suggest that the Indian life insurance industry exhibits considerable disparity among insurers in terms of technical efficiency, with scores ranging from 44.3 percent to 100 percent. The average level of technical efficiency among the 22 life insurers is

approximately 0.811. This means that an average life insurer needs only 81.1 percent of the inputs currently used if it operates on the efficient frontier rather than at its existing (virtual) location. The implication of this finding is that the Indian life insurance industry experiences technical inefficiency of around 18.89 percent. The evidence suggests that life insurers could achieve significant input savings, averaging at least 18.89 percent in equity capital, net commission and operating expenses, by adopting best-practice technology while maintaining the same level of outputs. Nevertheless, the scope for reducing inputs through the adoption of best practices differs from one insurer to another.

Among the 22 life insurers, 5 exhibit technical efficiency with an OTE score of 1. These insurers jointly form the efficient frontier and serve as the reference group for inefficient insurers. In the context of DEA, these insurers are referred to as peers and provide a benchmark of best operating practices for inefficient insurers to follow. In the Indian life insurance sector, Aegon, Aviva, Life Insurance Corporation, Reliance Nippon, SBI Life (see Table 3) are observed to be efficient insurers. The other 17 insurers record OTE scores below 1, indicating the presence of technical inefficiency. The findings therefore reveal considerable deviations of insurers from the best practice frontier. The efficiency of these insurers can be improved through a reduction in input utilization. For the inefficient insurers, OTE scores lie between 0.443 for Edelweiss Tokio and 0.879 for ICICI Prudential. It implies that Edelweiss Tokio and ICICI Prudential could reduce their existing input levels by 55.7 percent and 12.1 percent, respectively, without altering their level of outputs. A similar interpretation of OTE scores holds for the remaining inefficient insurers in the sample.

5.2 Decomposition of Overall technical efficiency: PTE and SE

As discussed in methodology that overall technical inefficiency is decomposed in the two categories: i) pure technical inefficiency (also known as managerial inefficiency) and ii) scale inefficiency. Pure technical inefficiency occurs due to the mismanagement of resources that reflects the incompetence of managers in reducing the management slacks and in achieving the maximum possible outputs. While, Scale inefficiency occurs due to the inappropriate scale size. There can be the two possible reasons of inappropriate scale size. First, it can occur due to the sub-optimal scale size which reflects that particular insurer is operating at increasing returns-to-scale (IRS). Alternatively, it can occur due to the supra-optimal scale size which reflects that particular insurer is operating at decreasing returns-to-scale (DRS). In DEA parlance, a DMU (i.e., life insurer in our case) that attain OTE score equal to one or OTIE equal to zero refers as a “*globally efficient*” unit and the insurers that attain PTE score equal to one or PTIE equal to zero refers as a “*locally efficient*” unit. In our case, on an average only nine insurers achieved the status of “*locally efficient*” unit as their PTE score equal to one. Among these, five insurers are “*globally efficient*” as they secured OTE score equal to one. In the remaining 13 life insurers (having $PTE < 1$), managerial inefficiency is evident, although the extent of inefficiency differs across insurers. In these, life insurers, OTIE is derived from both PTIE and SIE as their both PTE and SE scores are less than one. The grand mean of PTE scores is 0.885 which is less than the grand mean

of SE scores (0.917) that reflects overall technical inefficiency in Indian life insurance industry is largely occurring due to the underperformance of management rather than the inappropriate scale size.

5.3 Nature of returns to scale in the life insurance industry

An insurance firm is said to be fully efficient if it is operating at constant returns-to-scale (CRS) (i.e., at the most productive scale size (MPSS)). In the short run, insurers may exhibit increasing (IRS) or decreasing returns-to-scale (DRS). However, in the long run, insurers tend to move toward CRS by up-sizing (in case of IRS) or down-sizing (in case of DRS) their scale of operations to survive in competitive insurance market. This fact implies that life insurer may operate at sub-optimal or supra-optimal scale size and it could improve their level of efficiency by adjusting their scale size. From the table 3, we note that more than 76 percent inefficient life insurers are operating at increasing return to scale, indicating that upsizing is the appropriate strategy for these scale inefficient insurers.

5.4 Ranking Analysis

As earlier mentioned, under the basic CCR DEA model all efficient units get the efficiency scores equal to one. Therefore, it becomes impossible to discriminate or rank the efficient insurers with this conventional DEA model. So, in order to rank the efficient insurers, we have applied the TOPSIS approach. It is a distance-based approach that provides ranks to the efficient units by obtaining the best solution, where the best solution is that which considers the maximum distance from the ideal solution and minimum distance from the anti-ideal solution. The last column of Table 4 provides the ranking of the life insurers on the basis of their OTE scores using DEA plus TOPSIS technique for the entire study period. Such a ranking helps the policyholders or investors to select the appropriate insurance firm to insure the risk and to park their investment. From the given table, it has been observed that Reliance Nippon emerges as the best-performing insurer, followed by Aviva, Aegon, SBI Life and LIC. These firms optimally utilize their resources without any observable inefficiency. Companies with technical efficiency scores less than unity are ranked lower, reflecting the extent of inefficiency relative to the best-performing firms. For instance, insurers such as Bharti AXA and Edelweiss Tokio occupy the bottom positions, indicating significant scope for efficiency improvement. In sum, this ranking analysis enables policymakers, regulators, and firm management to identify leaders and laggards in operational efficiency and to benchmark performance against industry best practices.

Table 3: Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency Scores for life insurers operating in India: 2022/23										
Code	Life Insurers	TE Score	TIE (%)	PTE Score	PTIE (%)	SE Score	SIE (%)	RTS	Dominant source of inefficiency	Rank
L1	Aditya Birla Sunlife	0.817	18.3	0.837	16.3	0.976	2.4	IRS	PTIE	13
L2	Aegon	1.000	0	1.000	0	1.000	0	CRS	Fully Efficient	3
L3	Ageas Federal	0.851	14.9	1.000	0	0.851	14.9	IRS	SIE	9
L4	Aviva	1.000	0	1.000	0	1.000	0	CRS	Fully Efficient	2
L5	Bajaj Allianz	0.628	37.2	0.686	31.4	0.916	8.4	DRS	PTIE	20
L6	Bharti AXA	0.534	46.6	0.539	46.1	0.992	0.8	IRS	PTIE	21
L7	Canara HSBC OBC	0.823	17.7	0.997	0.3	0.825	17.5	IRS	SIE	12
L8	Edelweiss Tokio	0.443	55.7	0.545	45.5	0.814	18.6	IRS	PTIE	22
L9	Future Generali India	0.758	24.2	0.785	21.5	0.965	3.5	IRS	PTIE	16
L10	HDFC	0.867	13.3	0.907	9.3	0.955	4.5	DRS	PTIE	7
L11	ICICI Prudential	0.879	12.1	0.954	4.6	0.922	7.8	DRS	SIE	6
L12	India First	0.844	15.6	0.950	5	0.889	11.1	IRS	SIE	10
L13	Kotak Mahindra	0.769	23.1	0.777	22.3	0.990	1	DRS	PTIE	15
L14	LIC	1.000	0	1.000	0	1.000	0	CRS	Fully Efficient	5
L15	Max Life	0.803	19.7	0.829	17.1	0.968	3.2	IRS	PTIE	14
L16	PNB Metlife	0.737	26.3	0.786	21.4	0.937	6.3	IRS	PTIE	17
L17	Pramerica	0.829	17.1	1.000	0	0.829	17.1	IRS	SIE	11
L18	Reliance Nippon	1.000	0	1.000	0	1.000	0	CRS	Fully Efficient	1
L19	SBI Life	1.000	0	1.000	0	1.000	0	CRS	Fully Efficient	4
L20	Shriram Life	0.700	30	1.000	0	0.700	30	IRS	SIE	18
L21	Star Union Dai-ichi	0.866	13.4	1.000	0	0.866	13.4	IRS	SIE	8
L22	TATA AIA	0.695	30.5	0.881	11.9	0.788	21.2	IRS	SIE	19
Average		0.811	18.895	0.885	11.486	0.917	8.259			
SD		0.150	15.025	0.146	14.685	0.085	8.561			
Maximum		1	55.7	1	46.1	1	30			
Minimum		0.443	0	0.539	0	0.7	0			
Source: Author's calculations										

5.5 Peer analysis of the life insurance industry for the year 2022/23

5.5.1 Discrimination of efficient insurers

To discriminate the efficient DMUs Chen (1997) and Chen and Yeh (1998) proposed a method according to which efficient life insurers are discriminated in different-different groups on the basis of their peer counts in the “reference set”. The peer count, with which an efficient insurer appears in the reference set of inefficient insurers, represents the extent of robustness of that particular insurer relative to other efficient insurers. The higher the peer count, the more robust it is or vice-versa. In the year 2022/23 among the 22 life insurer 5 are relatively efficient and their efficiency scores are equal to one. It describes that these firms are utilizing the resources in an appropriate manner. However, efficient insurers with the low peer count or zero peer count in the reference set of an inefficient insurer are likely to hold a very unusual input/output mix; hence, these are not suitable example for inefficient insurers. In the DEA parlance, an insurer with zero peer count is termed as “efficient by default” as it does not constitute the attributes which are required for inefficient insurers to become efficient.

Table 4 provides reference set for the inefficient insurers along with the peer count of efficient insurers under the assumption of CRS. Based on the peer count values, efficient insurers are separated into three distinct categories: Highly Robust Life Insurers; Medium Robust Life Insurers and Marginally Robust Life Insurers. It has been observed that among the five efficient

insurers; Reliance Nippon scored the highest peer count (16) and hence it is classified as the highest robust life insurer or in other way, it can be contemplated as the global leader of the Indian life insurance industry. While Life Insurance Corporation (LIC) and SBI life insurers fall in the middle category as they have moderate degree of peer count. However, Aviva falls in the category of marginally robust life insurers. It is quite interesting to note that Aegon Prudential life insurer is efficient, but it doesn't fall in the reference set of inefficient insurers. This reveals that Aegon doesn't exemplify the best practices which are required for inefficient insurers to enhance their efficiency level. Thus, this insurer can be designated as “efficient by default”.

Table 4: Peer weights for inefficient firms and peer counts: 2022/23					
Inefficient life insurers	Reference set				
	L2	L4	L14	L18	L19
L1	-	-	0.017	0.626	0.050
L3	-	-	0.001	0.135	0.014
L5	-	1.176	-	1.358	0.161
L6	-	0.725	-	0.220	0.013
L7	-	-	0.008	0.165	0.040
L8	-	-	-	0.095	0.010
L9	-	0.786	-	0.135	-
L10	-	0.041	-	3.799	-
L11	-	0.199	0.005	2.115	0.380
L12	-		0.003	0.363	0.038
L13	-	0.367		0.809	0.157
L15	-	-	0.048	0.426	-
L16	-	-	0.009	0.483	-
L17	-	-	-	0.135	0.005
L20	-	-	-	0.258	0.006
L21	-	-	0.006	0.252	0.019
L22	-	-	0.042	-	-
Notes: L1 - Aditya Birla Sunlife; L2 - Aegon; L3 – Ageas Federal; L4 - Aviva; L5 -Bajaj Allianz; L6 - Bharti AXA; L7 - Canara HSBC OBC; L8 - Edelweiss Tokio; L9 - Future Generali India; L10 - HDFC; L11 - ICICI Prudential; L12 – India First; L13 - Kotak Mahindra; L14 - LIC; L15 - MaxLife; L16 - PNB Metlife; L17 - Pramerica ; L18 - Reliance Nippon; L19- SBI Life; L20 – Shriram Life; L21 - Star Union Dai-ichi; L22 - TATA AIA.					
Source: Author's calculations					

5.5.2 Discrimination of inefficient life insurers

To discriminate the inefficient units Kumar and Gulati (2008) proposed a criteria in their study according to which the inefficient life insurers are separated into different-different groups on the basis of their quartile values of OTE scores. In the present study, inefficient life insurers are categorized into four groups: (a) highly inefficient; (b) below average; (c) above average; and (d) marginally inefficient (see table 5). It is noteworthy that the insurer belonging to the ‘highly inefficient’ and ‘marginally inefficient’ category requires more attention. The ‘highly inefficient’ category includes those insurers which have been obtained the overall technical efficiency score

less than or equal to the value of the first quartile. The insurers of this category are classified as the most inefficient or worst performer insurers. This implies that these insurers are not utilizing the resources in an efficient way. Bajaj Allianz, Bharti AXA, Edelweiss Tokio, and TATA AIA life insurers fall in this category. Further, the life insurers which have secured OTE scores above the third quartile but less than the one are included in marginally inefficient category. Ageas Federal, HDFC, ICICI Prudential, Star Union Dai-Ichi lie in this category. This finding reflects that these insurers are operating at a high level of operating efficiency compare than other inefficient insurers even though they are not fully efficient. Thus, these insurers can attain the status of global leader, by bringing a little improvement in the resource utilization process.

Table 5: Categorization of Inefficient Life Insurance Firms: 2022/23			
Highly inefficient (TE ≤ Q₁)	Below average (Q₁ < TE ≤ Q₂)	Above average (Q₂ < TE ≤ Q₃)	Marginally inefficient (TE > Q₃)
Bajaj Allianz (5) Bharti AXA (6) Edelweiss Tokio (8) Tata AIA (22)	Future Generali India (9) Kotak Mahindra (13) Max Life (15) PNB Metlife (16) Shriram Life (20)	Aditya Birla Sunlife (1) Canara HSBC OBC (7) India First (12) Pramerica (17)	Ageas Federal (3) HDFC (10) ICICI Prudential (11) Star Union Dai-Ichi (21)
Notes: i) Q ₁ , Q ₂ and Q ₃ indicate the 1 st , 2 nd and 3 rd quartile, respectively; ii) Figures in brackets are ranks; iii) Q ₁ =0.698, Q ₂ = 0.803, and Q ₃ = 0.847			
Source: Author's calculations			

5.6 Targets setting for inefficient life insurers for the year 2022/23

The most important feature of DEA is that, it doesn't only ascertain that 'how much a firm is inefficient?' but also provides the sources of inefficiency. To identify the sources of inefficiency we obtained the potential input reduction and potential output augmentation for each inefficient life insurer utilizing the values of input and output targets. It is worth mentioning here that the target setting is only done for inefficient insurers. For insurer 'p', the input target of i^{th} input can be computed as:

$$x_{ip}^* = \theta_p^* x_{ip} - s_i^{-*} \quad i = 1, 2, \dots, m$$

After attaining the input target, the potential reduction in i^{th} input can be obtained as:

$$\text{Potential reduction of } i^{\text{th}} \text{ input} = \left(\frac{x_{ip} - x_{ip}^*}{x_{ip}} \right) \times 100$$

For insurer 'p', the output target of r^{th} output can be computed as:

$$y_{rp}^* = y_{rp} + s_r^{+*} \quad r = 1, 2, \dots, s$$

From the obtained output target, the potential augmentation in r^{th} output can be calculated as:

$$\text{Potential augmentation of } r^{th} \text{ output} = \left(\frac{y_{rp}^* - y_{rp}}{y_{rp}} \right) \times 100$$

Note here that ‘*’ indicates the optimum value of the variables under observation.

Table 6 provides the actual and target values of input and output variables along with the potential input reductions and potential output augmentations respectively for the inefficient insurers. From the input side, it has been observed that in each inefficient insurer, some degree of inputs reduction is feasible. However, there are huge variations in the magnitude of potential inputs saving across insurers. It has been noted that the potential reduction in equity capital (x_1) ranges between 12.05 percent and 55.67 percent. In two insurers, namely, Bharti AXA and Edelweiss Tokio, the potential to reduce equity capital to be more than 40 percent. However, the magnitude of potential reduction in equity capital is less than 15 percent in Ageas Federal, HDFC, ICICI Prudential, Star Union Dai-ichi. Therefore, in the remaining 11 inefficient insurers, the potential reduction in equity capital ranges from 15 to 40 percent. Further, we also noticed wide variations in the magnitude of potential reduction in net commission expenses (x_2) and operating expenses (x_3) across the inefficient insurers. The variations in the magnitude of potential reductions in net commission expenses and operating expenses were observed almost same as in the equity capital across the inefficient insurers.

Apart from this, moving to the output side, it has been observed that the potential augmentation in income from investment is feasible for all the inefficient insurers except in Ageas Federal and ICICI Prudential. The potential addition in income from investment ranges between 17.62 percent and 249.72 percent. In Canara HSBC OBC, MaxLife, Star Union Dai-ichi, TATA AIA, the potential for addition in income from investment is more than 100 percent from what they are currently producing.

Table 6: Actual and target values of input and output variables and potential reduction in inputs and potential addition in outputs: 2022/23

Inefficient life insurers	Actual Values of input and output variables					Targeted values of input and output variables					Potential output augmentation (%)		Potential input reduction (%)		
	Y1	Y2	X1	X2	X3	Y1	Y2	X1	X2	X3	Y1	Y2	X1	X2	X3
L1	1453945	369651	292610	84361	209650	1453945	707468	239070	68925	171289	0.00	91.39	18.30	18.30	18.30
L3	226148	85234	112111	10806	35831	226148	85234	95420	9197	30496	0.00	0.00	14.89	14.89	14.89
L5	1911540	481961	1078473	120667	389340	1911540	566902	677766	75833	244681	0.00	17.62	37.16	37.16	37.16
L6	287076	82240	391879	18828	92905	287076	113857	209435	10062	49652	0.00	38.45	46.56	46.56	46.56
L7	702972	140536	135307	41355	83623	702972	316877	111298	34017	68785	0.00	125.48	17.74	17.74	17.74
L8	165438	39852	264629	13616	57812	165438	62785	117301	6036	25626	0.00	57.54	55.67	55.67	55.67
L9	166781	45453	254620	6574	59274	166781	85010	193076	4985	37156	0.00	87.03	24.17	24.17	37.31
L10	5676401	1331726	1298681	288684	843738	5676401	2349443	1125587	250207	731281	0.00	76.42	13.33	13.33	13.33
L11	3855953	1084066	1009178	186389	458323	3855953	1084066	887561	163927	403090	0.00	0.00	12.05	12.05	12.05
L12	597364	130624	143346	31043	84425	597364	223958	121051	26215	71295	0.00	71.45	15.55	15.55	15.55
L13	1501845	308006	532873	81421	204584	1501845	397614	409820	62619	157341	0.00	29.09	23.09	23.09	23.09
L15	2488183	640797	354673	161384	358082	2488183	1552314	284778	129580	280120	0.00	142.25	19.71	19.71	21.77
L16	833394	227374	201712	51945	145177	833394	394322	148590	38265	106944	0.00	73.42	26.34	26.34	26.34
L17	145047	45405	121160	6025	32028	145047	57646	100391	4992	26538	0.00	26.96	17.14	17.14	17.14
L20	253886	59010	79671	15042	57722	253886	109574	55774	10530	40408	0.00	85.69	30.00	30.00	30.00
L21	549218	119372	106195	29877	75964	549218	265189	91935	25865	65763	0.00	122.15	13.43	13.43	13.43
L22	1997532	370590	276967	199621	437642	1997532	1296014	192458	107800	202893	0.00	249.72	30.51	46.00	53.64

Notes: L1 - Aditya Birla Sunlife; L3 – Ageas Federal; L5 -Bajaj Allianz; L6 - Bharti AXA; L7 - Canara HSBC OBC; L8 - Edelweiss Tokio; L9 - Future Generali India; L10 - HDFC; L11 - ICICI Prudential; L12 – India First; L13 - Kotak Mahindra; L15 - MaxLife; L16 - PNB Metlife; L17 - Pramerica ; L20 – Shriram Life; L21 - Star Union Dai-ichi; L22 - TATA AIA.

Source: Author’s calculations

6. Conclusions, policy implications and direction for future research

The foremost aim of this study is to examine the level of (in)efficiency in the Indian life insurance industry for the year 2022/23. The study also provided the strict ranking to the life insurers using TOPSIS approach. To ascertain the inputs and outputs, present study followed the value-added approach. The input vector contains three inputs: (a) equity capital, (b) net commission and (c) operating expenses while output vector contains two outputs: (a) net premium earned and (b) income from investment. To compute the OTE scores, we utilized the input-oriented CCR and BCC DEA models. The empirical findings indicate that on an average OTE scores among life insurers vary from 0.443 to 1, with a mean of 0.811. This implies that on an average there is a requirement of 18.89 percent reduction in all the inputs to produce the given level of outputs. Indian life insurers exhibit only moderate efficiency, indicating substantial scope for improving the utilization of equity capital, commission expenses, and operating expenses to generate net premiums and investment income. On an average only five life insurance firms namely Aegon, Aviva, LIC, Reliance Nippon, and SBI Life are fully efficient during the study year. Further, on exploring the sources of overall technical (in)efficiency, we note that the overall technical inefficiency in the Indian life insurance industry is primarily occurring due to incompetence of managers rather than the inappropriate scale size. Therefore, Indian life insurance companies require more focus on improving their management system relative to altering their scale size. The whatever scale inefficiency is occurring; it is primarily because of increasing return to scale that reflects Indian life insurance firms are too small to realize the benefits of economies of scale. Most of the scale inefficient insurers are requisite to expand their business operations to enhance the efficiency level.

Further, the results of ranking analysis revealed that Reliance Nippon got the top position, and Edelweiss Tokio is at the bottom. Additionally, we also carried out the target setting analysis for the financial year 2022/23. It has been observed that in each inefficient insurer, some degree of inputs reduction is feasible. However, there are huge variations in the magnitude of potential inputs saving across insurers. Furthermore, it has been observed that the potential augmentation in income from investment is feasible for all the inefficient insurers except in Ageas Federal and ICICI Prudential.

In sum, empirical results suggest that the inefficient insurers should pay more attention to improving their management system. These inefficient insurers should make efforts to optimize the use of capital and their day-to-day expenditures. Further, more focus is required to augment investment income rather than premium income in order to achieve the higher levels of efficiency by the life insurers. The future research work could be extended in various directions. First, we can extend the study for a longer time period and can measure the inter-temporal variations in the technical efficiency of the life insurers. Second, we can investigate the efficiency differences between life and non-life insurers by employing the meta-frontier approach. Third, using the panel data, we can also evaluate the total factor productivity growth of the Indian life insurers by applying MPI approach.

References

- Amri, K., Gattoufi, S., & Muharrami, S. (2012). Analyzing the Technical Efficiency of Insurance Companies in GCC. *The Journal of Risk Finance*, 13(4), 362-380.
- Anandarao, S., Durai, S. R. S., & Goyari, P. (2019). Efficiency Decomposition in Two-stage Data Envelopment Analysis: An Application to Life Insurance Companies in India. *Journal of Quantitative Economics*, 17(2), 271-285.
- Banker, R.D., Charnes, A., & Cooper, W.W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, 30(9), 1078-1092.
- Berger, A.N., Cummins, J.D., Weiss, M.A., & Zi, H. (2000). Conglomeration versus Strategic Focus: Evidence from the Insurance Industry. *Journal of Financial Intermediation*, 9(4), 323-362.
- Bhatia, A., & Mahendru, M. (2022). Revenue Efficiency Evaluation of Life Insurance Companies in India: Identification of Leaders and Laggards. *Benchmarking: An International Journal*, 29(10), 3133-3162.
- Bhatia, A., & Mahendru, M. (2023). Efficiency Appraisal of Life Insurance Industry in India- Public versus Private Players. *The Review of Finance and Banking*, 15(1), 65-81.
- Boonyasai, T., Grace, M.F., & Skipper, H.D. (2002). The Effect of Liberalization and Deregulation on Life Insurer Efficiency. Working Paper No. 02-2, Center for Risk Management and Insurance Research. Georgia State University, Atlanta, GA.
- Brockett, P.L., Cooper, W.W., Golden, L.L., Rousseau, J.J., & Wang, Y. (1998). DEA Evaluations of the Efficiency of Organizational Forms and Distribution Systems in the US Property and Liability Insurance Industry. *International Journal of Systems Science*, 29(11), 1235-1247.
- Chakraborty, J. (2016). Efficiency Analysis of Indian Life Insurance Firms: A DEA Investigation. *SCMS Journal of Indian Management*, 13(3), 5-24.
- Chakraborty, K., Dutta, A., & Sengupta, P.P. (2013). Efficiency and Productivity of Indian Life Insurance Industry. *Asia-Pacific Journal of Risk and Insurance*, 7(1), 1-26.
- Chakraborty, K., & Harper, R. K. (2017). Dynamic Productivity Analysis of Insurance Firms—The Effect of Firm-Specific and Macroeconomic Characteristics. *International Journal of Applied Economics*, 14(2), 37-55.
- Charnes, A., Cooper, W.W., & Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, 2(6), 429-444.

- Chen, T. (1997). An Evaluation of the Relative Performance of University Libraries in Taipei. *Asian Libraries*, 6(1/2), 39-50.
- Chen, T., & Yeh, T. (1998). A Study of Efficiency Evaluation in Taiwan's Banks. *International Journal of Service Industry Management*, 9(5), 402-415.
- Cooper, W.W., Seiford, L.M., & Tone, K. (2007). *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. Springer, New York.
- Cummins, J.D., & Xie, X. (2008). Mergers and Acquisitions in the US Property-Liability Insurance Industry: Productivity and Efficiency Effects. *Journal of Banking & Finance*, 32(1), 30-55.
- Cummins, J.D., & Zi, H. (1998). Comparison of Frontier Efficiency Methods: An Application to the U.S. Life Insurance Industry. *Journal of Productivity Analysis*, 10(2), 131-152.
- Diacon, S.R., Starkey, K., & O'Brien, C. (2002). Size and Efficiency in European Long-Term Insurance Companies: An International Comparison. *The Geneva Papers on Risk and Insurance*, 27(3), 444-466.
- Dutta, A. (2013). Impact of Privatization on Productivity: A Non-Parametric Analysis of Indian Insurance Sector. *Global Business Review*, 14(2), 297-314.
- Dutta, A., & Sengupta, P.P. (2011). Efficiency Measurement of Indian Life Insurance Industry in Post-Reforms Era". *Global Business Review*, 12(3), 415-430.
- Eling, M., & Luhnen, M. (2010). Frontier Efficiency Methodologies to Measure Performance in the Insurance Industry: Overview, Systematization, and Recent Developments. *The Geneva Papers on Risk and Insurance- Issues and Practices*, 35(2), 217-265.
- Garg, M. C., & Garg, S. (2020). Efficiency Evaluation of Indian General Insurance Companies. *IUP Journal of Management Research*, 19(1), 7-26.
- Hancock, D. (1985). The Financial Firm: Production with Monetary and Nonmonetary Goods. *Journal of Political Economy*, 93(5), 859-880.
- Hao, J.C.J., & Chou, L. (2005). The Estimation of Efficiency for Life Insurance Industry: The Case in Taiwan. *Journal of Asian Economics*, 16(5), 847-860.
- Huang, W., & Eling, M. (2012). An Efficiency Comparison of the Non-Life Insurance Industry in the BRIC Countries. *European Journal of Operational Research*, 226(3), 577-591.
- Hwang, C., & Yoon, K. (1981). *Multiple Attributes Decision Making: Methods and Applications: A State-of-the-Art Survey*. Springer, Heidelberg, Berlin.

- Hwang, C., Lai, Y., & Liu, T. (1993). A New Approach for Multiple Objective Decision Making. *Computers and Operational Research*, 20(8), 889-899.
- Jarraya, B., & Bouri, A. (2013). Multiobjective Optimization for the Asset Allocation of European Nonlife Insurance Companies. *Journal of Multi-Criteria Decision Analysis*, 20(3-4), 97-108.
- Kaffash, S., Azizi, R., Huang, Y., & Zhu, J. (2020). A Survey of Data Envelopment Analysis Applications in the Insurance Industry 1993–2018. *European Journal of Operational Research*, 284(3), 801-813.
- Kumar, S., & Gulati, R. (2008). An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks Using Data Envelopment Analysis. *Eurasian Journal of Business and Economics*, 1(2), 33-69.
- Parida, T. K., & Acharya, D. (2017). *The Life Insurance Industry in India*. Singapore. Springer Nature.
- Ray, S., Thakur, V., & Bandyopadhyay, K. (2020). India's Insurance Sector: Challenges and Opportunities. (Working Paper No. 394). Indian Council for Research on International Economic Relations. https://icrier.org/pdf/Working_Paper_394.pdf.
- Reyna, A.M., & Fuentes, H.J. (2018). A cost Efficiency Analysis of the Insurance Industry in Mexico. *Journal of Productivity Analysis*, 49(1), 49-64.
- Sen, S. (2020). Analysis of Cost Efficiency of Indian Life Insurers: A Comparison of Quantity vs Value Based DEA Approach. *Asia-Pacific Journal of Risk and Insurance*, 14(1), 1-25.
- Shetty, A., & Basri, S. (2020). Assessing the Technical Efficiency of Traditional and Corporate Agents in Indian Life Insurance Industry: Slack-Based Data Envelopment Analysis Approach. *Global Business Review*, 21(2), 490-506.
- Siddiqui, S. A., & Shaddady, A. (2023). How Profit Efficient is Indian Life Insurance Industry: A DEA Study. *SAGE Open*, 13(4), 1-13.
- Sinha, R. P. (2014). Policy Lapsation Risk and Technical Efficiency: Evidence from Indian Life Insurance Sector. *IUP Journal of Financial Risk Management*, 11(1), 25-33.
- Sinha, R. P. (2015). A Dynamic DEA Model for Indian Life Insurance Companies. *Global Business Review*, 16(2), 258-269.
- Sinha, R.P. (2017). Efficiency-solvency Linkage of Indian General Insurance Companies: A Robust Non-Parametric Approach. *Eurasian Economic Review*, 7(3), 353-370.
- Sinha, R.P., & Chatterjee, B. (2011). Technical Efficiency Behaviour of Life Insurance Companies: A Dynamic Panel Approach. *The Indian Economic Journal*, 59(1), 146-161.

- Tone, K. (2001). A Slacks-Based Measure of Efficiency in Data Envelopment Analysis. *European journal of operational research*, 130(3), 498-509.
- Tone, K., & Sahoo B.K. (2005). Evaluating Cost Efficiency And Returns To Scale In The Life Insurance Corporation Of India Using Data Envelopment Analysis. *Socio-Economic Planning Sciences*, 39(4), 261–285.
- Yoon, K. (1987). A Reconciliation among Discrete Compromise Solutions. *Journal of the Operational Research Society*, 38(3), 277-286.
- Yuengert, A. M. (1993). The Measurement of Efficiency in Life Insurance: Estimates of a Mixed Normal-Gamma Error Model. *Journal of Banking and Finance*, 17(2-3), 483-496.