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UNVEILING PRODUCTIVITY GROWTH IN INDIAN LIFE INSURANCE FIRMS THROUGH DATA ENVELOPMENT ANALYSIS

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Abstract: This study aims to examine total factor productivity (TFP) growth in the Indian life insurance sector from 2008–09 to 2017–18 using a non-parametric frontier methodology. The methodology's unique approach over a decade and nine observation windows provides insights into industry dynamics. Results indicate a negligible role of efficiency change, emphasizing the industry's reliance on technical advancements. The results are pivotal for industry stakeholders, policymakers, and researchers aiming to boost efficiency and competitiveness. The findings underscore the need for strategic adaptation to technological shifts and optimized managerial practices to drive sustainable productivity growth in the dynamic landscape of the Indian life insurance sector.

Keywords: Total factor productivity, non-parametric frontier methodology, technical change, efficiency growth, Indian life insurance sector

MSC: 90B50, 90C05.

1. INTRODUCTION

In the last few decades, the liberalisation of insurance markets across the globe has led to major structural and operational changes in the industry. The process of liberalising the insurance industry included changes in market access regulations, deepening of the market both in terms of scale and scope, and the removal of various tariff and non-tariff restrictions. These changes were accompanied by macroeconomic policy shifts leading to the replacement of financial repression by financial liberalisation, which lowered the interest margins generated by financial intermediaries. Inter alia, these two factors created pressures on the insurance sector profit margin, requiring enhanced attention to productivity and efficiency improvements in the insurance sector.

In light of insurance industry developments, studies employ frontier methodologies to analyze companies' productivity and efficiency relative to a constructed performance frontier derived from observed input and output data points. Apart from providing the validity of financial and economic hypotheses, the application of frontier estimation techniques provides additional insights to both the market regulators and the insurance company managers for assessing the impact of changes in market regulation policies (e.g., market unification, entry deregulation, or introduction of prudential regulations) and the justification for the adoption of strategies at the company level. Kaffash et al.[1] reviewed 132 research studies on the insurance sector (which were published between 1993 and 2018) with applications of DEA, covering both methodological aspects and applications. The study identified 76 research studies that explored the impact of idiosyncratic and exogenous variables like corporate governance, organisation structure, firm consolidation, deregulation of the industry, and intellectual capital on insurer efficiency and productivity change.

In the Indian context, researchers became intrigued by the performance of life and general insurance companies following the liberalization of the insurance sector.Several research papers [2,3,4,5,6] estimated the efficiency of Indian life insurance companies using diverse models such as new cost efficiency, window analysis, dynamic DEA, and two-stage network DEA. Several other research papers [7,8,9] estimated the total factor productivity growth of Indian life insurers.

In our research, spanning two decades of meticulous analysis, we delve into the total factor productivity (TFP) growth of 21 prominent life insurance companies in India. Employing a unique sequential performance frontier methodology, our study covers a substantial temporal span from 2008 to 2018, segmented into nine observation windows for a comprehensive understanding of the dynamics at play. The key revelation of our investigation is the predominant role played by technical change in driving productivity growth over the examined period. Notably, the contribution of efficiency change to overall productivity gains emerges as negligible, underscoring the nuanced interplay of factors shaping the industry's trajectory. This nuanced insight into the components of productivity growth offers invaluable implications for strategic decision-making within the Indian life insurance sector, providing a foundation for future research and policy considerations in this critical domain.

Moreover, our methodological innovation distinguishes this study from existing research on Indian life insurance companies. Unlike conventional studies employing contemporaneous frontiers, our estimation of the Malmquist productivity index is grounded in a sequential frontier, eliminating the technical regress problem encountered previously. By decomposing technical change into input-biased, output-biased, and the magnitude of technical change, our study provides additional insights into the nature of technical transformations during the observed period. Furthermore, the exploration of the linkage between productivity shift parameters and environmental variables introduces a novel dimension to the analysis, shedding light on the indirect influences shaping productivity growth. Our methodological advancements and substantive findings will contribute to the existing literature on life insurance productivity, offering a new paradigm for future research in this vital sector.

The paper unfolds into the following five distinct sections: Section 2 describes the insurance literature landscape. Section 3 unveils the methodology and data used. Section 4 delves into the presentation and analysis of the results, and Section 5 presents the conclusion.

2. LITERATURE REVIEW

In this comprehensive review of intertemporal productivity and efficiency within the life insurance industry, we draw upon a rich body of literature to contextualize our research.

Donni and Fecher (1997) [10] set the stage by examining efficiency and productivity changes across 15 OECD countries, attributing substantial productivity growth to technical progress. Fukuyama (1997) [11] contributed insights into Japanese life insurance companies, revealing significant total productivity growth in the mutual group driven by technical progress, while the stock group experienced limited gains. Bernstein [12] explored the Canadian life insurance landscape, dissecting total factor productivity growth into contributions from changes in returns to scale and the rate of technical growth. Barros et al. [13] added complexity by evaluating Portuguese insurers, uncovering performance divergence influenced by contextual variables such as asymmetric market information distribution and variations in scale and scope economies. Barros, Necktarios, and Peypoch [14] applied the Luenberger index to Greek life insurance companies, emphasizing technical progress as the primary driver of average annual productivity growth. Mahlberg and Url [15] turned their attention to German insurers, highlighting technical progress and improvements in scale efficiency as catalysts for productivity growth. Bertoni and Croce [16] broadened the scope, investigating the drivers of insurance productivity across five European countries and concluding that best practice innovation significantly contributed to total factor productivity growth. Vencappa et al. [17] expanded the analysis to European insurers, revealing the adverse impact of stochastic macroeconomic shocks on the sector. Biener et al. [18] brought a nuanced perspective by estimating the efficiency and total factor productivity of Swiss insurance firms, signaling divergent performance trends in different sectors. Ohene Asare et al. [19] explored the growth dynamic cost productivity in Ghana, highlighting the impact of insurance regulation on cost productivity.

In the Indian context, Sinha [20] pioneered the assessment of total factor productivity growth in 13 life insurance companies, revealing positive productivity changes. Sinha and Chatterjee [21] delved into the intertemporal efficiency movement, emphasizing performance disparities between LIC and private insurers. Chakraborty, Dutta, and Sengupta [8] continued the exploration of productivity growth among 14 life insurers, while Siddiqui [22] investigated the productivity growth performance of 24 companies, attributing a significant portion to technical progress.

Against this backdrop, our research stands out as a seminal contribution to the field. Covering two decades and 21 prominent Indian life insurance companies, our study employs a unique sequential performance frontier methodology. Unlike conventional contemporaneous frontiers, our approach addresses the technical regress problem by grounding the estimation of the Malmquist productivity index in a sequential frontier. Furthermore, our exploration of the linkage between productivity shift parameters and environmental variables introduces a novel dimension to the analysis, shedding light on the indirect influences shaping productivity growth.

3. METHODOLOGY AND DATA

In the present section, we provide a brief elaboration of the non-parametric method of estimation, a description of the input and output variables, and data sources.

3.1 Productivity estimation

The ratio of the quantity of output generated by a decision-making unit to the amount of input consumed is known as its productivity. Because it directly affects business performance and raises living standards, productivity is significant from a managerial and social perspective. Thus, productivity growth analysis is important both at the macro and micro level, as it helps to review performance, critically analyse pitfalls, and initiate necessary corrective measures.

Among various methodologies, four pivotal approaches underscore productivity measurement: the growth accounting approach, the index approach, the econometric approach, and the non-parametric approach. In the present study, we have applied the non-parametric approach, which computes the changes in total factor productivity with the aid of distance functions. The concept of distance function was introduced by Shephard [23,24,25], which provides a functional representation of multiple output-multiple input technologies requiring information only on the physical quantities of inputs and outputs. A firm's distance from the production frontier is determined by an output distance function, while its distance from the optimal input frontier is determined by an input distance function. To be more specific, the distance function-based approach decomposes productivity change into two major components: movements in the direction of the frontier and changes within it. The non-parametric approach has several advantages over three other competing approaches. First, the non-parametric mathematical programming-based method is capable of handling multiple outputs; thus, one need not be confined to cases of cost or revenue functions only. Second, in this approach, one need not assume any specific functional (parametric) form relating outputs to inputs.

3.2 The contemporaneous and the sequential Malmquist index of productivity change

Among non-parametric measures, the MPI (Malmquist Productivity Index) reigns supreme in popularity. Malmquist [26] introduced the concept of the construction of quantity indices as the ratio of distance functions. Caves et al. [27] applied the concept in the context of the estimation of the productivity index.

For elaborating the methodology, we consider a production relation P involving the transformation of inputs x (=x_1,x_2,....,x_n) on to outputs y ((=y_1,y_2,....,y_m)

Where $x \in R_+^N$ and y $\in R_+^M$.

Thus, the technology can be described as:P=[(x,y): x ≥X,y≤Y]

Where the reference set of inputs and outputs is indicated by X and Y, respectively.

The output distance function can be defined as follows:

$D_{output}(x, y) = \inf\{\mu: (x, \frac{y}{\mu}) \in P\} = [\sup\{\varphi: (x, \varphi y) \in P\}]^{-1}$

An observed firm is inefficient or efficient depending on whether $D_{output}(x, y) <$ 1or=1.In

The Malmquist index for two consecutive time periods, t and t+1, can be expressed as the geometric mean of the distance function ratios, which are computed using the frontiers of the corresponding time periods. Thus the index of productivity change may be written as:

$M_{t,t+1} = [\frac{D^t(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^{t+1}(x_t, y_t)}]^{\frac{1}{2}}$

Where x_i and y_i represent the input and output sets for period i.

The estimation method introduced by Färe and Grosskopf, Lindgren and Roos [28,29] is based on the construction of a contemporaneous frontier. Thus the implicit assumption is that in period i, only the current period technology is feasible. This assumption is unrealistic and often results in providing negative technical change estimates. A sequential production frontier [30,31], on the other hand, assumes that in period i, previous period technologies as well as the current period technology are feasible to the producer. Thus for period t, the reference set for performance evaluation $\bar{P}_t = P_1(x_1, y_1) \cup P_2(x_2, y_2) \cup \ldots \cup P_t(x_t, y_t) = \{(x, y) | y \leq \bar{Y}_t, x \geq \bar{X}_t\}$. Where $\bar{X}_t$ and $\bar{Y}_t$ represent the sequential reference input and output sets respectively.

Thus the sequential frontier is constructed from a panel(of inputs and outputs)whose size increases with the progress of time. Such a frontier eliminates the possibility of experiencing technical regress over time which is a more realistic assumption. Shestalova [32] pointed out that a sequential frontier is less affected (compared to a contemporaneous frontier) by the presence/absence of a particular observation in the data set.The corresponding distance function may be written as:

$DSEQ_t^o(x, y) = \inf\{\mu: (x, \frac{y}{\mu}) \in \bar{P}_t\} = [\sup\{\varphi: (x, \varphi y) \in \bar{P}_t\}]^{-1}$

Where $DSEQ_t^o(x, y)$ is the sequential distance function in period t.

Nishimizu and Page [33] decomposed the productivity change into two components: technical change and changes in technical efficiency. Efficiency change and technical change were the two components that Färe et al. [28,29] separated out of the output-based Malmquist index. In case of sequential frontier,

Efficiency Change $= \frac{DSEQ_o^{t+1}(x_{t+1}, y_{t+1})}{D_{output}^t(x_t, y_t)} = \Delta E(x_t, y_t, x_{t+1}, y_{t+1})$

Technical Change $= [\frac{DSEQ_o^t(x_{t+1}, y_{t+1})}{DSEQ_o^{t+1}(x_{t+1}, y_{t+1})} \text{ X } \frac{DSEQ_o^t(x_t, y_t)}{DSEQ_o^{t+1}(x_t, y_t)}]^{\frac{1}{2}} = \Delta T(x_{t+1}, y_{t+1})$

Two components that can be separated out of the technical change index are the magnitude index and the bias index [34]. In case of sequential frontier,

$\Delta T(x_{t+1}, y_{t+1}) = \Delta T(x_t, y_t) Bias_I(x_t, y_t, x_{t+1}, y_{t+1})$

$= [\frac{DSEQ_o^t(x^t, y^t)}{DSEQ_o^{t+1}(x^t, y^t)}][\frac{DSEQ_o^t(x^{t+1}, y^{t+1})}{DSEQ_o^{t+1}(x^{t+1}, y^{t+1})} / \frac{DSEQ_o^t(x^{t+1}, y^t)}{DSEQ_o^{t+1}(x^{t+1}, y^t)}]$

Thus, the technical change part has two components. The first component$\Delta T(x^t, y^t)$ represents the magnitude (of technical change) for the period t. The second component$Bias_I(x^t, y^t, x^{t+1}, y^{t+1})$ shows the bias (of technical change), which is the proportion between the technical change magnitudes for periods t+1 and t. The magnitude index is an indicator of the relative distance between the frontiers of period t+1 and period t respectivelywhen observed in period t. The bias index, which makes up the second component, calculates how much the relative distance between the two frontiers changed between the period t+1 observation and the period t observation. The contribution of bias index towards technical change is positive, zero or negative depending on whether the magnitude (of technical change) measured from period t+1 data is greater than, equal to orless than themagnitude(of technical change) measured from period t data.

The bias index represented above can be decomposed in to two sub-components, an index of the output bias$O_{bias}(\mathbf{y}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ and an index of the input bias$I_{bias}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{x}^{t+1})$. Here $O_{bias}(\mathbf{y}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ evaluates how much the distance between the two frontiers—which correspond to periods t+1 and t, respectively—has changed relative to each other. To be more specific ,O_{bias} $(\mathbf{y}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ takes into account the input vector from period t+1 and the output vector from the two time periods. If the input vector is kept fixed at $\mathbf{x}^{t+1}$, O_{bias} $(\mathbf{y}^t,\mathbf{x}^{t+1},y^{t+1})$ is the ratio of the technological change's magnitude along a ray for the period $\mathbf{y}^{t+1}$to the magnitude of technical change along a ray for $\mathbf{y}^t$, and consequently it provides an estimate of the output bias. $I_{bias}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{x}^{t+1})$ involves the output vector from period t and the input vectors from both periods. Keeping the output vector constant at $\mathbf{y}^t$, $I_{bias}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{x}^{t+1})$ is the ratio of the magnitude of technical change $\mathbf{x}^{t+1}$ to the magnitude (of technical change) for $\mathbf{x}^t$, and thus yields an estimate of the input bias.

The estimation of the two components of bias index is significant for analyzing the technical change in a more meaningful manner. In the presence of input and output bias, the impacts of technical change are asymmetric across the inputs and outputs. Thus, the estimates of bias enable us to understand the nature of technical change from the input and output composition change perspective.

3.3 Variables and data

Evaluation of efficiency and total factor Productivity change using the frontier approach requires specification and selection of inputs and outputs, as their performance is evaluated based on their observed ability to transform inputs into outputs. However, since the insurance sector provides financial services, outputs are non-tangible in nature and not always easy to define. For any financial service industry (like banking, life insurance, and non-life insurance), the input-output transformation activity can be viewed from different angles, and the choice of input and output indicators is contingent on the viewpoint adopted. Three primary input types were recognised by Eling and Luhnen [35] as being utilised in the insurance industry: capital (debt and equity capital), business services (travel, communications, and advertising), and labour (agents and office workers). Leverty, Tyler, and Grace [36] identified three standpoints for output selection: the financial intermediation approach [37], the user cost approach [38,39], and the value-added approach. [40,41]. The financial intermediation approach considers financial service providers as intermediaries providing a link between investors and borrowers. The value-added approach treats such activities as firm outputs that generate significant value added

Three categories of services are provided by insurance businesses, according to the value-added approach: financial services, financial intermediation, and risk-sharing and risk mitigation. Some of the empirical studies [based on the value-added approach] have used net premiums as value-added, while some other research studies have used benefits paid and changes in reserves as output indicators [42]. According to user cost approach, an indicator is either treated as an output or an input based on its net contribution to the insurer's income.

The present study considers two inputs, namely, premium income (net) and operating expenses, and three outputs, including net benefits paid to the policyholders, sum assured, and total assets under management (table 1). Premium mobilisation is the key to the generation of revenue. Since we do not have adequate information about the detailed expenses on labour and overheads, we have taken operating expenses as the proxy indicator. The net benefits paid show the policyholders' real outflow, whilst the sum assured indicates the coverage offered to them. The asset under management is an indicator of the financial health of the insurer. A higher level of assets under management provides more scope for earning investment income.

Table 1: Inputs and outputs

Indicator	Input/Output
Operating Expenses	Input
Net Premium Income	
Sum Assured	
Benefits paid to the policyholder	Output
Total asset under management	

Source: Selected by the authors.

The data includes 21 life insurers. In the productivity estimating model, every life insurer is treated as a Decision-Making Unit (DMU), and the study period is set between 2008–09 and 2017–18. The data for the study is a panel of observations in which each insurer forms the cross section, and the study period forms the time series. This study adapts sequential Malmquist data envelopment analysis to determine firms' total factor productivity under variable returns to scale, considering both input and output orientations.

4.RESULTS AND ANALYSIS

4.1 Productivity Growth Parameters: A Descriptive Statistical Overview

Table 2 presents crucial descriptive statistics for total factor productivity shift (TFPC) and its components—efficiency change (EC) and technical change (TC). It also includes the breakdown of technical change into magnitude (MATC), output-biased (OBTC), and input-biased (IBTC) components, spanning the period from 2009-10 to 2017-18.

Table 2: Descriptive Statistics of Productivity Growth Parameters

Particulars	TFPC	EC	TC	MATC	OBTC	IBTC
Mean	1.1753	0.9999	1.1519	1.0742	1.0382	1.113
Median	1.0844	1.0000	1.1140	1.0846	1.0082	1.001
Standard Deviation	0.6797	0.1936	0.3970	0.229	0.152	0.703
Skewness	7.8362	1.2484	5.8335	-1.653	7.982	9.149
Kurtosis	81.296	3.2502	55.723	7.259	70.361	94.931
Maximum	8.6756	1.7695	5.1203	1.704	2.462	9.126
Minimum	0.0892	0.5127	0.0892	0.0096	0.906	0.933
Range	8.5864	1.2568	5.0311	1.694	1.557	8.193

Source: Calculated.

Table 2 reveals that on an average, total factor productivity change has gone up by 17.5%. The efficiency changes component of total factor productivity declined over the period. On the other hand, technical change for the industry has gone up by 15.19% respectively. Technology is not Hicks-neutral as can be seen by the magnitude of change in bias index. Change in total bias is mostly contributed by the input side as it has contributed more than 11% and the remaining (nearly 4%) has been contributed by output biased technical change. This implies that technical progress is largely caused by improvement in input efficiency than increases in output capability. The table also provides information about other measures of descriptive statistics (standard deviation, skewness, and kurtosis) indicating the degree of variability, asymmetry and peakedness of the distribution of the measures.

4.2 Decomposition of total factor productivity change

Table 4 outlines the year-wise dynamics of the three technical change components: magnitude of technical change, input-biased technical change, and output-biased technical change. The data suggests that, except for the 2014–15 to 2016–17 periods, output-biased technical change and magnitude of technical change have predominantly driven technical change during the specified period. Figure 2 offers a visual comparison.

Table 3: Yearly variations in mean productivity components

Particulars	2010	2011	2012	2013	2014	2015	2016	2017	2018
EC	1.003	0.999	1.009	1.078	0.998	0.994	1.027	1.001	0.899
TC	1.024	1.354	1.243	1.229	1.129	1.347	1.030	0.907	1.107
TFPC	1.036	1.378	1.253	1.321	1.126	1.478	1.079	0.929	0.992

Source: Calculated.

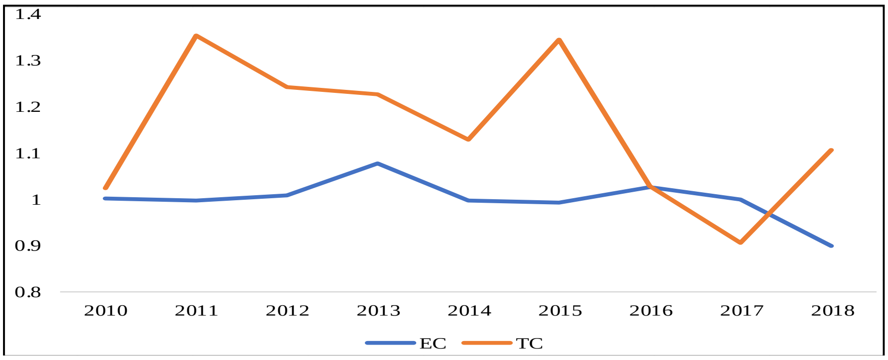

Figure 1: Mean efficiency change and technical change

4.3 Sources of technical change

Table 4 presents the year-wise movements in the three components of technical change: magnitude of technical change, input-biased technical change, and output-biased technical change. The table indicates that during the period under consideration, except for the phases 2014–15 to 2016–17, technical change has been caused mainly by output-biased technical change and the magnitude of technical change. Figure 2 provides a graphical comparison.

Table 4: Sources of technical change (2009-10 to 2017-18)

Particulars	2010	2011	2012	2013	2014	2015	2016	2017	2018
IBTC	1.058	0.999	1.015	1.011	1.014	1.185	1.091	1.639	1.009
OBTC	1.027	1.107	1.008	1.128	1.006	1.014	1.020	1.019	1.020
MATC	0.977	1.227	1.218	1.144	1.109	1.115	0.934	0.861	1.077
TC	1.024	1.354	1.243	1.229	1.129	1.347	1.030	0.907	1.107

Source: Calculated.

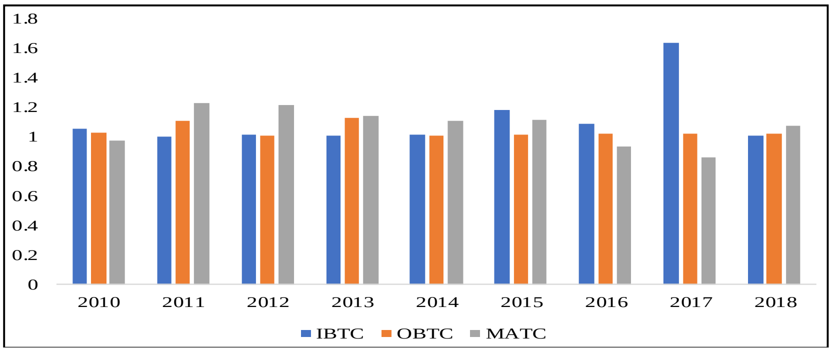

Figure 2: Sources of technical change

4.4 Insurer wise trends in productivity change

Table 5 presents the insurer-wise results of mean productivity change and its two components: mean efficiency changes and mean technical change. It is interesting to observe that all the observed life insurers (except DHFL Pramerica) have registered positive productivity growth during the in-sample period. Of these 20 insurers, 11 exhibited more than 10% mean productivity growth, while the remaining exhibited average productivity growth ranging from 5% to 9%. HDFC Life remained an outlier as it registered an 86% improvement in total factor productivity. As indicated earlier, technical change remained the main driving force behind productivity change. Figure 3 visually depicts changes in productivity, technical elements, and efficiency.

Table 5: Insurer wise productivity growth performance

Life Insurer	Mean Productivity Growth	Mean Efficiency Change	Mean Technical Change
Aditya Birla Sunlife	1.1186	0.9991	1.1429
Aegon	1.3229	1.0000	1.4022
Aviva	1.2481	1.0481	1.1978
Bajaj Allianz	1.1300	1.0001	1.1653
Bharti AXA	1.0871	0.9510	1.1349
Canara HSBC OBC	1.1107	1.0588	1.0609
DHFL Pramerica	0.9133	0.8551	1.1085
Future Generali	1.3717	0.9909	1.1183
HDFC Standard	1.8642	1.0198	1.4867
ICICI Prudential	1.3548	1.0726	1.2425
IDBI Federal	1.1488	1.0156	1.1780
Kotak Mahindra	1.0746	0.9479	1.1363
LIC	1.0541	1.0000	1.0718
Max Life	1.0655	0.9496	1.1486
PNB Metlife	1.0644	0.9439	1.1276
Reliance Nippon	1.2342	1.0639	1.1786
Sahara India	1.099	1.0053	1.1175
SBI Life	1.1575	1.0937	1.0788
Shriram Life Insurance	1.0843	0.9288	1.2283
Star Union Dai-ichi	1.0845	1.0539	1.0216
Tata AIA	1.0890	0.9995	1.0765

Source: Calculated.

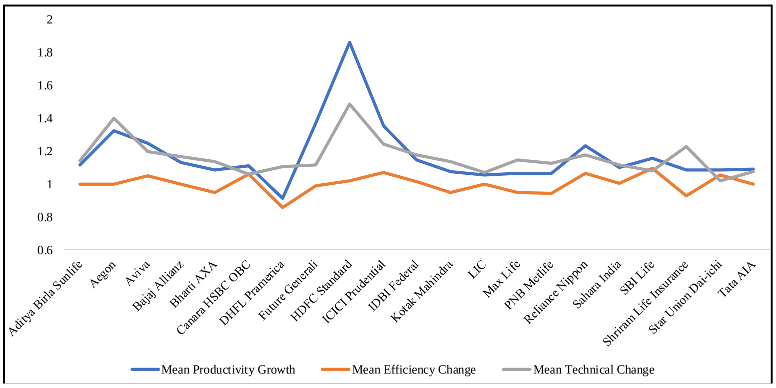

Figure 3: Change in average productivity across life insurers

4.5 Composition of technical change

The insurer-wise mean values for the three components of technical change—output-biased, input-biased, and extent of technical change—are shown in Table 6. Out of the 21 life insurers, only one firm has performed negatively in terms of output-biased technical change. Out of the remaining 20 insurers, 4 life insurers (Future Generali and Bajaj Allianz) registered more than 5% growth in terms of output-biased technical change, while the remaining 16 exhibited growth between 0% and 5%. In terms of technical change, three life insurers (ICICI Prudential, Bharti AXA, and Tata AIA) performed way ahead of the others. 13 life insurers exhibited improvement in input-biased technical change, while the remaining exhibited regress. Finally, 18 out of the 21 in-sample life insurers exhibited improvement in the magnitude of the technical change. Eleven life insurers demonstrated an increase in technical change of over 10%.

A graphical representation of the insurer-wise performance of the technical change components is shown in Figure 4.

Table 6: Insurer wise performance of technical change components

Life Insurer	Output Biased Technical Change	Input Biased Technical Change	Magnitude of Technical Change
Aditya Birla Sunlife	1.0022	0.9991	1.1260
Aegon	1.0362	1.0782	1.1875
Aviva	1.0087	1.0130	1.1660
Bajaj Allianz	1.0678	1.0106	1.0438
Bharti AXA	1.0237	0.9993	1.1258
Canara HSBC OBC	0.9937	0.9997	1.0619
DHFL Pramerica	1.0144	1.0765	1.1089
Future Generali	1.3242	1.2666	0.8812
HDFC Standard	1.0566	1.7689	0.9695
ICICI Prudential	1.0231	2.1038	1.0080
IDBI Federal	1.0002	1.0026	1.1378
Kotak Mahindra	1.0152	0.9981	1.1141
LIC	1.0561	1.0561	0.9487
Max Life	1.0078	1.0002	1.1201
PNB Metlife	1.0144	0.9957	1.1219
Reliance Nippon	1.0154	0.9945	1.1163
Sahara India	1.0432	1.0079	1.0494
SBI Life	1.0323	0.9966	1.0425
Shriram Life Insurance	1.0230	1.0056	1.1240
Star Union Dai-ichi	1.0140	0.9924	1.0422
Tata AIA	1.0306	1.0055	1.0629

Source: Calculated.

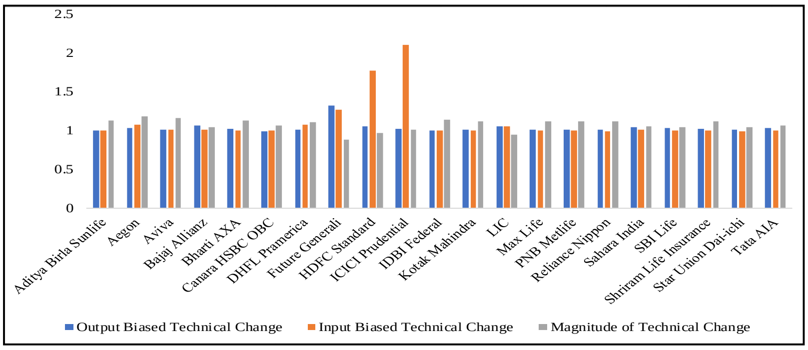

Figure 4: Components of technical change

4.6 Influence of environmental variables

In the present study, we have regressed the Malmquist index and its components on three environmental variables: solvency ratio, expense ratio (ratio of underwriting expenses to net premium income), and commission ratio (ratio of commission expenses to net premium income). The solvency ratio of an insurer is the key metric for assessing its ability to meet its long-term debt obligations. The expense ratio is another important measure of the financial viability of the concerned insurer, as it indicates whether the insurance company is earning more premium than it is spending to earn the premium or not.

In the regression analysis, we have dropped two life insurance companies (Aditya Birla Sunlife and Sahara Life) due to the non-availability of information about the explanatory variables for the period under observation. Tables 7 to 9 present the regression results for three dependent variables: Malmquist index, efficiency change, and technical change. Since the dependent variables are bounded from below as the lower limit of productivity, we have used the log of the variables as the dependent variables for the three models. As the data structure is in panel format, we have used the Hausman test to find out the comparative suitability of fixed and random effects models, and based on the results, we have chosen the fixed effects model.

Table 7: Regression of Malmquist index on environmental variables

Particulars	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*
Intercept	0.1009	0.1413	0.7139	0.4845
Solvency Ratio	0.0029	0.0245	0.1182	0.9072
Expenses Ratio	−0.3777	0.0908	−4.159	0.0006
Commission Ratio	1.6946	1.9178	0.8836	0.3886

Source: Calculated.

Table 8: Regression of Efficiency Change index on environmental variables

Particulars	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*
Intercept	0.0261	0.0719	0.3631	0.7207
Solvency Ratio	−0.0039	0.0154	−0.2518	0.8040
Expenses Ratio	−0.0300	0.0507	−0.5908	0.5620
Commission Ratio	−0.4072	0.7879	−0.5168	0.6116

Source: Calculated.

Table 9: Regression of Technical Change index on environmental variables

Particulars	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*
Intercept	0.0747	0.1171	0.6385	0.5312
Solvency Ratio	0.0068	0.0279	0.2427	0.8109
Expenses Ratio	−0.3477	0.0971	−3.579	0.0021
Commission Ratio	2.1014	1.2869	1.6330	0.1199

Source: Calculated.

The tables show that, for the two regressions with the Malmquist index and the technical change index, respectively, only the coefficient of expenses ratio is statistically significant (at 95% level of significance) among the three variables included as explanatory variables in the three models. No explanatory variable is found to have significantly influenced efficiency change for the observed period. The sign of the coefficients of solvency ratio is found to be positive for Malmquist index and technical change but negative for efficiency change. The coefficients of commission ratio, on the other hand, are positive for Malmquist and technical change index but negative for efficiency change index.

5. CONCLUSION

This research contributes to the understanding of total factor productivity growth in the Indian life insurance sector over the period 2008–09 to 2017–18. Utilizing a unique sequential performance frontier methodology, we identified that technical change played a predominant role in driving productivity growth, while the contribution of efficiency change was found to be negligible. Our study extends over a decade, providing a comprehensive analysis through nine observation windows, offering nuanced insights into the industry's dynamics.

Despite these contributions, the study is not without limitations: 1) The study focus on a 10-year period may not fully capture long-term trends and could limit the generalizability of findings; 2) The inclusion of only three contextual variables may oversimplify the multifaceted nature of the insurance sector, potentially neglecting important influencing factors; 3) The study did not account for the impact of structural changes, such as regulatory shifts or market dynamics, which could have influenced the observed productivity trends; 4) While using cumulative data as the reference set reduced sensitivity to outlier firms, it may have introduced biases that need further investigation and 5) The study's broad analysis may overlook nuances at the individual firm level, limiting the depth of insights into specific company dynamics.

We also propose the following future research directions: 1) to investigate how the managerial ability and leadership within insurance companies impact their productivity results, exploring the role of executives in shaping efficiency as in Cvetkoska et al. [43]; 2) to examine how productivity growth patterns vary between short-term and long-term perspectives, identifying factors that contribute differently over various time horizons; 3) to examine how the adoption of artificial intelligence (AI) and advanced technologies by insurance companies influences their productivity results, considering the evolving technological landscape; 4) to compare the productivity growth of Indian insurance companies with those in other countries to identify potential areas for improvement and international best practices and 5) to conduct a dynamic analysis to understand the impact of structural changes over time, considering regulatory shifts, market dynamics, and industry-specific transformations. These future research directions aim to provide a more comprehensive understanding of the factors influencing productivity growth in the Indian insurance sector, offering valuable insights for strategic decision-making and contributing to the development of efficient and competitive industry practices.

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