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Estimating Revenue Efficiency in Indian General Insurance Companies: A Semi-parametric Econometric Approach

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Abstract: In the realm of general insurance in India, an econometric investigation was conducted to estimate the revenue efficiency across a selection of 15 prominent, diversified general insurance entities for the fiscal years 2011-12 to 2016-17. Utilizing a semi-parametric methodology, the revenue frontier was constructed under the GAM framework, while the variance components were estimated employing the method of moments. This analysis further explored the influence of revenue efficiency on critical profitability metrics, namely return on equity (ROE) and return on assets (ROA), through the application of instrumental variable regression. The findings provide pivotal insights into the dynamics of revenue efficiency and its consequential impact on the financial performance of general insurance companies in India, offering a substantial contribution to the literature on insurance economics and the methodology of efficiency measurement. The research underscores the significance of adopting semi-parametric models for a nuanced understanding of revenue efficiency, thus paving the way for enhanced strategic decision-making in the insurance sector.

Keywords: Revenue efficiency; General additive models; Semi-parametric approach; instrumental variable regression

1 Introduction

In a modern society, the general insurance industry plays a crucial role in the economy by protecting the property, liability and health of its citizens. General insurance includes all forms of insurance except life insurance. The major kinds of general insurance include: (i) property insurance (against events like fire, burglary or theft); (ii) personal insurance (against health disorders, travel and accidents); and (iii) liability insurance (including public, product and professional liability insurance).

In the Indian context, the size of general insurance in relation to the total insurance market is relatively small; general insurance accounts for around 22% of the total insurance market in India. However, the industry has tremendous potential for expansion in view of the growing need to protect properties and agricultural produce from natural calamities (or incidents like a fire breakout), protect businesses and individuals against contingent liabilities and provide a cushion against rising health care costs.

In the post-reform phase, several research studies attempted to assess the efficiency and performance of the general insurance companies using a non-parametric framework and most of them attempted to estimate the technical efficiency of the general insurers. The present study, in contrast, adopted a different approach. In the first stage, a revenue frontier of the in-sample general insurance companies has been constructed using a semi-parametric General Additive Model-Stochastic Frontier Analysis (GAM-SFA) approach wherein the frontier is estimated by applying the GAM and the variance parameters are obtained by using pseudo-likelihood estimators. In the second stage, the relationship between important profitability parameters and revenue efficiency estimates is explored in terms of regression with an instrumental variable. The study has five sections and proceeds as follows: Section 1 provides a brief overview of the Indian general insurance industry. Section 2 reviews the extant literature on general insurance performance. Section 3 outlines the methodology. Section 4 relates to the data, results and discussion. Section 5 is the conclusion.

2 General Insurance Industry in India

However, the origin of the industry is quite old. The modern form of general insurance business was first established in pre-independent India when Triton Insurance Co. Ltd. was formed in 1850. This was followed by the establishment of the Bombay Mutual Life Insurance Society in 1870 and the Oriental Assurance Company in 1880. Subsequently, many general insurance companies were formed in India. Thus, there were more than 100 general insurance companies in India at the time of its nationalization in 1973 when the industry was nationalized. The process of nationalization involved the establishment of the General Insurance Corporation as the state-sponsored reinsurance company and the formation of four state-sponsored general insurance companies (by amalgamating 107 private general insurers).

In the 1990s, India embraced an open market economy with a greater role for the private sector. Financial sector reform was an integral part of the reform process which was initiated with banking sector reform involving the deregulation of private sector entry and the introduction of prudential regulations for banking operations. At the same time, the Government of India set up a high-powered committee on the Indian insurance sector (headed by Shri R. N. Malhotra) to examine the existing scenario and recommend appropriate measures for boosting competitive efficiency and strengthening the regulatory framework. The Committee recommended deregulation in both the life and general insurance markets. Private sector players started entering the general insurance market in 2000 and by March 2017, the total number of general insurance companies had increased to 31. During the post-liberalisation phase, the sector witnessed significant growth in terms of premium growth, asset management and the branch network of the insurance companies. Table 1 provides a brief overview of the growth observed in the sector between end-March 2012 and end-March 2017. Table 2 provides the movements in insurance penetration (ratio of aggregate insurance premium to GDP), insurance density (ratio of insurance premium to total population) and incurred claims ratio (ratio of total paid claims to total premium collected) during the same period.

Table 1. Overview of the Indian general insurance industry

Particulars	2012	2013	2014	2015	2016	2017
Number of general insurance companies (including reinsurers)	28	28	29	29	30	31
Number of offices	7050	8099	9,872	10407	10803	11141
Number of new policies issued (jn lakhs)	857	1070	1048	1202	1257	1525
Gross direct premium (Rs crores)	54578	65023	79934	87151	99333	130971
Asset sunder management (Rs crores)	99268	122992	149536	172144	188126	222344

Source: Handbook of Insurance Statistics for various years from the Insurance Regulatory and Development Authority (IRDA).

Table 2. Performance indicators of the Indian general insurance industry

Particulars	2012	2013	2014	2015	2016	2017
Insurance penetration	0.78	0.8	0.7	0.7	0.70	0.77
Insurance density	10.5	11	11	11	11.5	13.2
Incurred claim ratio	88.89	82.79	76.54	73.58	74.44	84.38

Source: Handbook of Insurance Statistics for various years from the IRDA.

3 Related Work

The present section briefly outlines the important research studies related to general insurance companies, both in the international and Indian contexts. Section 2.1 provides a brief summary of the international research studies while Section 2.2 describes the Indian studies.

3.1 International Studies

Toivanen [1] estimated the economies of scale and scope for the Finnish non-life insurance industry for the period 1989-91. The study identified two types of costs (operating costs and costs arising from incurred claims) related to production and portfolio management functions. The study suggested that the creation of a branch network is important for acquiring market power or informational advantages since it helps captivate customers from the standpoint of portfolio management. The study confirmed the existence of diseconomies of scale at the firm level, economies of scale at the branch level and economies of scope in production. Fukuyama and Weber [2] estimated the efficiency and productivity growth of Japanese non-life insurance companies for the period 1983-1994. They estimated output-oriented technical efficiency and the Malmquist index of total factor productivity change. The productivity change estimate was further decomposed into indices of efficiency change and frontier shift. The study found significant productivity improvement during 1983-90 which was mainly contributed by technological change. In the next three years, technological change stagnated (due to the collapse of the bubble economy) but started improving again by 1993-94.

Ennsfellner et al. [3] examined the production efficiency of the Austrian insurance market for the time period 1994-1999. The study used a Bayesian stochastic frontier for estimating the aggregate and firm-specific efficiency of the in-sample insurance companies. The study found that the process of deregulation of the Austrian insurance market had influenced the productive efficiency of the insurers in a positive manner.

Choi and Weiss [4] examined the performance of the US property-liability industry using a stochastic frontier approach.In particular, the study examined the linkage between firm performance, market structure and efficiency in property-liability insurers during 1992–1998.The study estimated both cost and revenue efficiency and tested the validity of three specific hypotheses: traditional structure-conduct-performance, relative market power, and efficient structure. The results obtained from the aforementioned study provided support for the efficient structure hypothesis. According to the efficient structure hypothesis, more efficient firms are able to charge lower prices than competitors. This permits them to get larger market shares and extract economic rents, resulting in increased concentration in the industry. Thus, as per the study, insurance regulators should be more concerned about efficiency compared to relative market power.

Yang [5] applied a two-stage non-parametric model for evaluating the efficiency of the Canadian life and health insurance industry. His study includes two separate models for the computation of production and investment efficiency for both input- and output-oriented models. In the second stage of the study, a dummy input with value 1 was used and the production and (inverse of) investment efficiency scores were used as outputs. This model thus involved the integration of production and investment performance for the observed insurance companies. The evidence obtained from the study indicated that the life and health insurance industry in Canada operated fairly efficiently during the in-sample period.

Kao and Hwang [6] applied a relational and independent two-stage Data Envelopment Analysis (DEA) model to evaluate the performance of 24 non-life insurance companies in Taiwan using average data for 2001 and 2002. The study decomposed the activity of insurance firms into two sub-processes: marketing (intermediate stage) and investment (final stage). The study showed that efficiency in the investment sub-process was lower than in the first-stage activity (marketing). Cummins and Xie [7] studied the effects of mergers and acquisitions in the US property-liability insurance industry on the productivity and efficiency of the insurers using data from 1994–2003. The results suggested that mergers and acquisitions in property-liability insurance increased the valuation of the concerned insurers. Their study found that acquiring insurers achieved more revenue efficiency gains than non-acquiring companies, and target firms exhibited greater cost and allocative efficiency growth as compared to the companies which were not targeted.

Barros et al. [8] used two-stage conditional performance benchmarking for the efficiency evaluation of 71 Greek life and non-life insurance companies. The study assumed that returns to scale were constant for the period under evaluation (1994-2003). The first-stage results of the study exhibited significant divergence in efficiency performance for the in-sample time span. The second-stage regression results showed that while competition is a major influencing factor of efficiency in the Greek insurance industry, but the degree of competition was not enough to improve market efficiency during the period. Mahlberg and Url [9] examined the efficiency and productivity impact of market unification on the German insurance companies for the period 1991-2006. Their study estimated the technical, revenue, cost efficiency and total factor productivity of 202 insurance companies under non-increasing returns to scale. The study provided a mixed picture regarding the convergence of performance among the observed insurance companies.

Cummins and Xie [10] examined efficiency, productivity and scale economies in the US property-liability insurance industry. The study analysed efficiency and change in total factor productivity using DEA. The results showed that the majority of the insurers below median size in the industry exhibited increasing returns to scale, and the majority of the insurers above median size exhibited decreasing returns to scale. Jarraya and Bouri [11] investigated profit efficiency and optimal production targets for the European non-life insurance industry for the period 2002-2008.They used the directional distance function for the computation of profit efficiency and the Lagrangean function for the specification of an optimal production plan. The study estimated the parameters of a stochastic technology frontier constructed from a sample of 175 non-life insurance companies. On the basis of the optimal quantity of inputs, desirable outputs and undesirable outputs generated from their model, the study proposed inefficiency indices for profit and production factors.

Alhassan and Biekpe [12] estimated the efficiency, productivity and returns to scale of South African non-life insurance companies for the period 2007-2012. They employed DEA for estimating efficiency, returns to scale and Malmquist total factor productivity change for the aforementioned period. They applied truncated bootstrapped and logistic regression techniques for identifying the determinants of efficiency and the probability of operating under constant returns to scale. The results showed that non-life insurers operated with about 50 percent efficiency. Approximately 20 percent of insurers were scale-efficient. The study also found productivity improvements during the period which were mainly due to technological changes. The results of the regression analysis indicated a non-linear impact of size on efficiency and constant returns to scale. Variables like product line diversification, reinsurance and leverage also had a significant relationship with efficiency and constant returns to scale.

Ferro and Leon [13] applied SFA to estimate the technical efficiency of Argentine non-life insurance companies for the period 2009-2014. The study applied two models: a time-invariant inefficiency model and time-varying decay model. The results indicated a low average of technical efficiency, a stagnated efficiency level during the later phase of the observed time period and a negative technical change.

3.2 Indian Studies

Mandal and Ghosh [14] estimated the technical efficiency of 12 general insurance companies in India for the period 2006-07 to 2009-10 using DEA. The study sought to assess the impact of the global economic slowdown on the general insurance sector. Sinha [15] used a dynamic DEA framework for estimating the dynamic efficiency performance of Indian general insurance companies. In a second study, Sinha [16] estimated the efficiency of Indian general insurance companies for 2013-14 using the conditional performance benchmarking method. Ilyas and Rajasekharan [17, 18] estimated the efficiency, total factor productivity and returns to scale of the Indian non-life insurance industry over the period 2005-2016. The first study [17] found that the Indian non-life insurance industry was moderately technical, scaled, cost-effective, and allocatively efficient. The second study [18] found (using the Fare-Primont index) that the non-life insurance sector exhibited a very low level of total factor productivity. The total factor productivity growth observed during the observed period (2005-2016) is mainly attributable to scale-mix efficiency.

The present study takes a different approach in the estimation of the efficiency performance of the in-sample general insurance companies in two respects. First, it seeks to estimate the revenue efficiency of the observed general insurers which has not been attempted so far in the existing literature. Second, the current study adopts a relatively novel approach to the estimation of efficiency.

4 Methodology

This section outlines the methodological development related to the estimation of stochastic frontiers and also outlines the regression method applied in the second stage.

4.1 Frontier Production Function and Estimation Methodology

Neoclassical economics defines a production function as one which relates the maximum producible level of output to a fixed bundle of inputs. Thus, for practical purposes, one can think of an industry production function which implies a frontier of potential output corresponding to the given input level while individual production functions may vary from the frontier because of variations in the scale of operation or heterogeneity in organizational structure. However, in the conventional econometric approach, the average production function was estimated as the representative of the industry production function. Farrell [19] defined the technical efficiency of an industry with respect to a given efficient isoquant as the weighted average of the technical efficiency of the corresponding isoquants of the constituent firms. A major weakness of this average approach is that the performance of a firm is compared with the average performance and not the best practice firm. Initial efforts were made by Aigner and Chu [20] using linear and quadratic programming with single equations and two-stage least squares techniques. For a production function $Y = f(X;\beta)$, Y is the maximum producible output from X (a non-stochastic input vector), and β represents the unknown vector of parameters to be estimated. The authors suggested two alternative minimization programs: (i) $\mathrm{Min} \mid Y_i - f(X_i;\beta)$ subject to $Y_i \leq f(X_i;\beta)$, and (ii) $\mathrm{Min}\,[Y_i - f(X_i;\beta)]^2$ subject to $Y_i \leq f(X_i;\beta)$. However, the results obtained were highly sensitive to the outliers [21]. Therefore, the econometric model of $Y_i = f(X_i;\beta) + \epsilon_i$ was considered.

The error term can be decomposed into $\epsilon_i = u_i + v_i$, where v_i represents a symmetric disturbance term which exhibits an independent and identical distribution (iid) as $N\left(0, \sigma_v^2\right)$, u_i represents a one-sided disturbance term ($u_i \leq 0$) and is derived from a distribution $(0, \sigma_u^2)$, which is truncated above 0. The residual of the estimate of the aforementioned model is $\hat{\epsilon}_i = Y_i - f\left(X_i;\hat{\beta}\right)$. Meeusen and van den Broeck [22] introduced an efficiency model $Y_i = \theta(X_i)\,E_i U_i$,, where E_i is a measure of efficiency distributed in the range (0,1), and U_i is a disturbance term distributed in the range (0,α).However, one needs to have separate estimates of u_i and v_i. Jondrow et al. [23] provided a procedure for the estimation of individual efficiency scores for a particular point (x, y) on the production frontier. The total variance is decomposed into the sum total of variances of u and $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $u_*(\mathrm{x}) = -\frac{\sigma_u^2 \epsilon}{\sigma^2}$, $\sigma_*^2 = \frac{\sigma_u^2}{\sigma^2}\sigma_v^2$. For the conditional distribution of $u(u \mid \epsilon) \sim N\left(u_*, \sigma_*^2\right)$, the variable is truncated at 0. For getting a point estimate of technical inefficiency, either the mean or mode of the distribution can be used. In addition, the result $-\frac{\mu_*}{\sigma_*} = \frac{\epsilon\lambda}{\sigma}$ can be obtained with $\lambda = \frac{\sigma_u}{\sigma_v}$.

The initial contributions to the stochastic frontier literature considered cross-sectional models and thus did not consider the impact of technical inefficiency changes over time. Cornwell et al. [24] and Kumbhakar [25] introduced stochastic frontier models in which technical inefficiency changes over time. They considered that firm effects are a quadratic function of time with coefficients varying across firms with a multi-variate distribution. In the Kumbhakar model [25], technical inefficiency is assumed to be a product of a well-defined deterministic function of time and a non-negative time-invariant effect which varies across firms. Battese and Coelli [26] introduced a stochastic frontier model in which firm effects are an exponential function of time. Battese and Coelli [27] introduced a more general model in which technical inefficiency effects are a function of idiosyncratic variables and time.

Fan et al. [28] introduced a semi-parametric frontier model, in which the functional form of the production frontier is unspecified, and the distribution of the composed error terms isin the known form as follows:

$$Y_i = g\left(X_i\right) + \epsilon_i \left(\epsilon_i = v_i - u_i\right)$$

where, X_i is a vector of regressors, $g(X_i)$ represents an unknown smooth function, ϵ_i is a composed error term including a two-sided statistical noise and a one-sided error term representing technical inefficiency.

The probability density function of ϵ is as follows:

$$f(\epsilon) = \frac{2}{\sigma}\varphi\left(\frac{\epsilon}{\sigma}\right)\left[1 - \psi\left(\epsilon\lambda\sigma^{-1}\right)\left(-\alpha \le \epsilon \le \alpha\right)\right.$$

where, $\sigma^2 = \sigma_u^2 + \sigma_v^2, \lambda = \frac{\sigma_u}{\sigma_v}$, and $\varphi(.)$ and $\psi(.)$ are the standard normal density and distribution functions, respectively. The conventional stochastic frontier approach requires the specification of an explicit functional form for relating output to input levels. In order to overcome this lack of flexibility, Vidoli and Ferrara [29] introduced a GAM framework. GAMs were proposed by Hastie and Tibshirani [30] which extended the conventional likelihood-based regression models and introduced a method for estimation. In the case of General Linear Model (GLM), the linear model $Y_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i$ is replaced with $\beta_0 + \sum_{i=1}^{n} f_i\left(X_i\right)$, with $f_i(.)$ as the smooth function.

In the present study, the GAM-based stochastic frontier approach is used to construct the revenue frontier and estimate efficiency. The variance parameters are estimated using Fan et al. [28].

4.2 Linkage with Working Parameters of Performance

An important part of the present study is to explore how the measures of revenue efficiency explain the profitability indicators of the in-sample general insurance companies. For this, an appropriate regression model has to be formulated with efficiency measured as the explanatory variable. However, revenue efficiency cannot be estimated directly. The estimate obtained depends significantly on the methodology being used. Further, the efficiency variable is stochastic in nature. In such cases, the instrumental variable method can be used, with the explanatory variable semi-replaced by another variable, which is correlated with the explanatory variable instead of the error term.

To explain the instrumental variable method in brief, the following regression model is considered:

$$Y_i = \beta_0 + \beta_1 X_i + U_i$$

where, Y_i, X_i and U_i represent the explained variable, the explanatory variable and the error term, respectively.

Now another variable, Z, is considered, which is correlated with X instead of the error term. The instrumental variable estimator of the slope (β_1) may be defined as

$$\bar{\beta}_1^{I\bar{V}} = \frac{\text{Cov}(Y, X)}{\text{Cov}(Z; X)}$$

where, $\bar{\beta}_1^{I\bar{V}}$ is a consistent estimator of the slope provided $Cov(Z.X)$ is non-zero. $\bar{\beta}_1^{I\bar{V}}$ is related to the true estimate of the slope in the form of $\bar{\beta}_1^{I\bar{V}} = \beta_1 + \frac{Cov(Z,U)}{Cov(Z,X)}$. If $Cov(Z,U) = 0$, then $\bar{\beta}_1^{I\bar{V}} \cong \beta_1$.

5 Data, Variables and Estimation Framework

5.1 Description of Variables

Estimation of revenue frontiers and revenue efficiency requires the identification of inputs, outputs and prices. However, specification of input and output variables (and price parameters) in the context of a general insurance industry is a difficult proposition because of the complexities involved in defining the indicator variables.

Eling and Luhnen [31] identified three major types of inputs used in the insurance industry: labour (including agents and office staff), business services (including items such as travel, communications and advertisement) and capital (including debt and equity capital). On the output side, Leverty and Grace [32] found three alternative approaches for choosing outputs: the financial intermediation approach, the user cost approach and the value-added approach. In the context of banking and other financial intermediaries engaged in fund-based activities, this approach treats financial service firms as intermediaries who bridge the gap between demanders and suppliers of funds. The value-added approach considers those activities as outputs which contribute significant value as assessed using operating cost allocations [33]. Broadly speaking, the value-added approach assumes that the insurers provide three major services: risk-pooling and risk-bearing, real financial services and intermediation. Some studies have used net premiums as valued added while others have used incurred benefits and changes in reserves as output proxies [34].

The present study seeks to construct a revenue frontier. Therefore, the major activities need to be identified, which contribute to insurer revenue as well as the inputs of service production. The problem in the Indian context, however, is the absence of very detailed information about variables which may be used as inputs and outputs for the estimation of revenue frontiers and revenue efficiency. Since very detailed information on various inputs cannot be obtained separately, two inputs are considered: total operating expenses and assets under management. The first input is considered as the proxy input for capturing operational activities which are required to generate premium. The second input captures the investment activities of general insurance companies. On the output side, net premium income and income from investments are considered as the two outputs. For all the outputs, price is taken as unity. Table 3 provides an overview of inputs, outputs and prices.

Table 3. Inputs, outputs and prices

Description	Input	Output
Operating expenses	√	-
Assets under management	√	-
Cross-section dummy	√	-
Time series dummy	√	-
Total income=net premium income+investment income	-	√

5.2 Data for Estimation

The present study covers the period 2011-12 to 2016-17. The data relating to the indicator variables have been collected from two sources: the Annual Reports of the IRDA for the respective years and the Handbook of Indian Insurance Statistics for 2014-15 and 2016-17.

5.3 Model Formulation

In the present study, two models of estimation of revenue frontiers are considered as follows:

$$\mathrm{Ln}(Y) = f\left[\mathrm{Ln}\left(X_1\right), \mathrm{Ln}\left(X_2\right), \mathrm{Ln}\left(X_3\right), \mathrm{Ln}\left(X_4\right)\right]$$
$$\mathrm{Ln}(Y) = f\left(X_1, X_2, X_3, X_4\right)$$

In the first model (Model 1), logarithmic values of the output and input variables are considered. In the second model (Model 2), logarithmic values of only the output variable are considered. For both models, a two-step procedure is used for the construction of the frontier. In the first step, GAM is used for constructing the frontier and computing efficiency. In the second step, variance parameters are obtained by the procedure.

5.4 Estimation Outcomes

This section presents efficiency scores from the two models, parameter coefficients, goodness of fit, variance component estimates and linkage with two important measures of profitability (ROE and ROA).

5.4.1 Descriptive statistics of efficiency scores

Table 4 provides the mean and standard deviation of efficiency scores for the two models estimated (presently) for the observation period (2011-12 to 2016-17). The mean efficiency scores for the two models revealed fluctuating trends during the observed time span. Thus, mean efficiency scores declined between 2011-12 and 2012-13, improved in the next financial year (2013-14) and declined for the next two years (2014-15 and 2015-16), In the last year under observation, mean scores improved somewhat in the first model while continuing the declining trend in the second model. The detailed results relating to revenue efficiency scores are included in Tables A1 and A2 in the appendix.

Information about how technical efficiency varies across public and private sector general insurers is obtained. Table 5 provides a comparison of the mean technical efficiency scores of observed public and private sector general insurers with respect to the two models.

Table 4. Descriptive statistics of revenue efficiency of the in-sample general insurers

Model	Descriptive Statistics	2012	2013	2014	2015	2016	2017
Model 1	Mean	0.8070	0.7966	0.8404	0.8278	0.7815	0.7993
	Standard deviation	0.1533	0.0981	0.0553	0.0807	0.1041	0.0857
Model 2	Mean	0.8210	0.8091	0.8267	0.8195	0.7885	0.7821
	Standard deviation	0.1406	0.0932	0.0450	0.0644	0.0951	0.0993

Source: Calculated by the author

Table 5. Mean revenue efficiency of the in-sample public and private sector general insurers

Model	Category	2012	2013	2014	2015	2016	2017
Model 1	Public sector	0.8348	0.7864	0.8057	0.7595	0.7974	0.8357
	Private sector	0.7969	0.8003	0.8531	0.8526	0.7758	0.7860
Model 2	Public sector	0.8197	0.8216	0.8127	0.8175	0.8521	0.8309
	Private sector	0.8215	0.8045	0.8318	0.8202	0.7654	0.7643

Source: Calculated by the author

Table 5 shows that there is not much difference in technical efficiency across ownership categories, irrespective of the model considered for estimation. The difference is even less if the average of the six in-sample years is taken. However, the relative performance of public and private sector general insurance companies varies across the two models chosen for estimation.

5.4.2 Efficiency density plots

Based on the estimates derived from the application of GAM-SFA, efficiency density plots can be generated. The density plots estimated with respect to the two models (Model1 and Model 2) are presented in Figure 1. Subgraph (a) of Figure 1 shows the efficiency density plot for Model 1 while subgraph (b) of Figure 1 presents the density plot for Model 2.

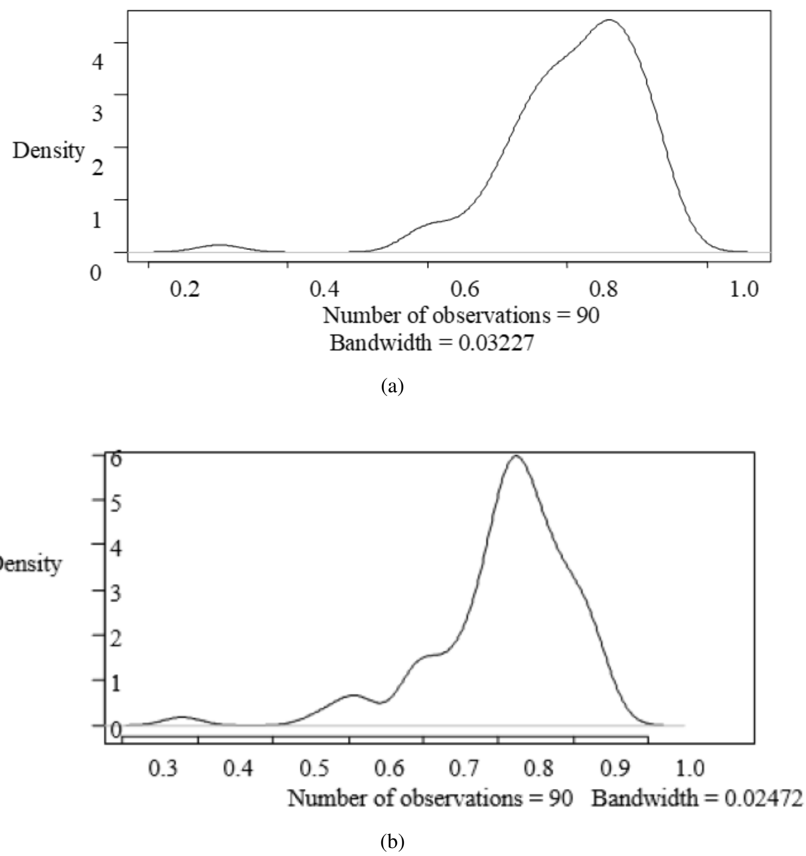

Figure 1. Efficiency density plots for Models 1 and 2: (a) Efficiency density plot for Model 1; (b) Efficiency density plot for Model 2

5.4.3 Estimation of technical (revenue) inefficiency

Stochastic frontier models include two error terms representing random (white noise) error (v) and technical inefficiency (u). Because of the presence of v, there are random deviations from the revenue frontier. On the other hand, it implies that there can be one-sided (negative) deviations from the boundary of the revenue frontier, which is defined by the best practices of insurers. Table 6 presents the estimates of technical inefficiency for the two models. Tables A3 and A4 in the Appendix present the year-wise and insurer-wise estimates.

Table 6. Mean technical (revenue) inefficiency of the in-sample general insurers

Model	2012	2013	2014	2015	2016	2017
Model 1	0.2419	0.2348	0.1759	0.1936	0.2553	0.2296
Model 2	0.2168	0.2184	0.1917	0.2021	0.2450	0.2541

Source: Calculated by the author.

5.4.4 Estimates of parametric coefficients with respect to Models 1 and 2

Table 7 provides estimates of parametric coefficients with respect to the two models. For both models, the coefficients are statistically significant.

Table 7. Parametric coefficients of the two models

Model	Coefficient	Standard Error	Coefficient/Standard Error	Probability of a Type 1 Error
Model 1	11.85	1.34	8.841	≈ 0
Model 2	11.48	0.2506	45.8	≈ 0

Source: Calculated by the author.

5.4.5 Goodness of fit and model validation

In the case of a linear regression model, the goodness of fit is indicated by the residual sum of squares. However, in the case of GAMs, the sum of squares does not make much sense as a measure of the discrepancy between the observations and the fitted values. Instead, the discrepancy in terms of deviance can be measured.

$$D = 2\left[L\left(\hat{\beta}_M\right) - L\left(\hat{\beta}_O\right)\right]\varphi$$

where, $L\left(\hat{\beta}_M\right)$ is the maximum likelihood of the saturated model, $L\left(\hat{\beta}_O\right)$ is the maximum likelihood of the observed (fitted) model, and Φ is the scale parameter.

In a statistical analysis, model validation is tested by cross-validation which involves out-of-sample testing. The main objective of cross validation is to test the ability of the chosen model to predict new data which was not used in the estimation process. The process of cross-validation involves partitioning the data into two complementary subsets: one that is used for performing the analysis and another that is used for model testing. Several rounds of cross-validation are usually performed in order to reduce variability in outcomes. In the present case, the Generalised Cross-Validation (GCV) score of the GAM fitted is computed. Smaller values of GCV indicate better model fitting.

Table 8 compares the outcomes of the two models used in the present study. A comparison of the results indicates that Model 1 exhibits slightly better goodness of fit compared to Model 2.

Table 8. Goodness of fit for the two models

Particulars	Model 1	Model 2
Adjusted R^2	0.95	0.939
Deviance explained	95.5%	94.5%
GCV	0.0538	0.0672
Scale estimate	0.0484	0.0598

Source: Calculated by the author.

5.4.6 Variance component estimates

Table 9 presents the variance component estimates for the two models. The table presents the overall standard deviation $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$ and the ratio of the standard deviation of one-sided and symmetric disturbance terms $\lambda = \frac{\sigma_u}{\sigma_v}$. The results imply that the total standard deviation is slightly lower in the first model compared to the second one. Further, the ratio of the standard deviation due to internal factors and external factors is higher in Model 1 relative to Model 2.

Table 9. Estimates of variance components

Particulars	Model	Estimate
Lambda (λ)	Model 1	2.3543
Sigma (σ)		0.3077
Lambda (λ)	Model 2	1.7865
Sigma (σ)		0.3214

Source: Calculated by the author.

5.4.7 Linkage with ROE and ROA

A part of this research enquiry is to explore the relationship of profitability measures (ROE and ROA) with revenue efficiency. However, owing to the existence of omitted variables, the application of ordinary least squares cannot be fruitful as the efficiency variable is correlated with the error term of the model. Therefore, the instrumental variable method of regression is applied. The solvency ratio is used as the instrumental variable, which has a very low correlation with the dependent variables (ROE and ROA) but is highly correlated with the explanatory variable. Tables 10 through 13 present the instrument variable regression outcomes for the two models. To be more specific, Table 10 presents the results with respect to Model 1 with ROE as the dependent variable. Table 11 presents the results for Model 2 with ROA as the dependent variable. Tables 12 and 13 represent the results for Model 2 with the dependent variables being ROE and ROA, respectively.

Table 10. Instrumental variable regression of ROE on efficiency (Model 1)

Particulars	Coefficient	Coefficient Lower Bound	Coefficient Upper Bound	Standard Error	t-ratio	Probability of a Type 1 Error
Constant	-0.3869	-0.8208	0.4096	0.2214	-1.748	0.0840
Efficiency	0.9750	0.0469	1.5405	0.2885	3.380	0.0011

Source: Calculated by the author.

Table 11. Instrumental variable regression of ROA on efficiency (Model 1)

Particulars	Coefficient	Coefficient Lower Bound	Coefficient Upper Bound	Standard Error	t-ratio	Probability of a Type 1 Error
Constant	-0.0262	-0.0939	0.0415	0.0346	-0.7590	0.4499
Efficiency	0.1403	0.0542	0.2263	0.0439	3.193	0.0020

Source: Calculated by the author.

Table 12. Instrumental variable regression of ROE on efficiency (Model 2)

Particulars	Coefficient	Coefficient Lower Bound	Coefficient Upper Bound	Standard Error	t-ratio	Probability of a Type 1 Error
Constant	-0.4165	-0.7727	-0.0603	0.1817	-2.292	0.0243
Efficiency	1.0127	0.5268	1.4986	0.2479	4.085	< 0.0001

Source: Calculated by the author.

Table 13. Instrumental variable regression of ROA on efficiency (Model 2)

Particulars	Coefficient	Coefficient Lower Bound	Coefficient Upper Bound	Standard Error	t-ratio	Probability of a Type 1 Error
Constant	-0.0305	-0.0756	0.0147	0.0230	-1.324	0.1891
Efficiency	0.1457	0.0868	0.2046	0.0301	4.847	< 0.0001

Source: Calculated by the author.

6 Conclusion

The study provides revenue efficiency estimates for fifteen major general insurance companies operating in India over a six-year period (2011-12 to 2016-17). Since a common inter-temporal stochastic frontier has been constructed for the estimation of revenue efficiency, performance is comparable over the time horizon. However, no definite trend could be identified. Similarly, the overall mean efficiency for the private and public sector general insurance companies is almost similar. On the aggregate, approximately 20 percent inefficiency is identified, which implies there is room for further improvement for both private and public sector companies.

The study is limited to fifteen major diversified general insurance companies and excludes the standalone health insurers operating in India. Further, the study is limited to a six-year span only. Inter alia, the analysiscan be extended in these two directions in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there is no conflict of interest.

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Appendix

Table A1. Revenue efficiency scores for Model 1

Insurer	2012	2013	2014	2015	2016	2017
Bajaj Allianz	0.7363	0.7883	0.8517	0.9008	0.8630	0.8162
Cholamandalam	0.9210	0.8952	0.8452	0.8035	0.6841	0.7559
Future Generali	0.8892	0.8992	0.9020	0.8486	0.7862	0.7002
HDFC Ergo	0.7690	0.7332	0.7947	0.7086	0.5883	0.6212
ICICI Lombard	0.8736	0.8759	0.7992	0.8242	0.6635	0.7293
IFFCO Tokio	0.8573	0.8218	0.8675	0.9344	0.9074	0.9243
Reliance	0.7168	0.7611	0.8344	0.8540	0.8008	0.7472
Royal Sundaram	0.8953	0.8485	0.9098	0.8863	0.8568	0.8606
SBI General	0.3017	0.5881	0.7522	0.7793	0.6174	0.7677
Shri Ram General	0.9331	0.7267	0.9404	0.9117	0.9068	0.9170
Tata AIG	0.8722	0.8654	0.8864	0.9268	0.8592	0.8064
National	0.8498	0.6692	0.8275	0.7634	0.8025	0.8032
New India	0.8055	0.9612	0.8453	0.8639	0.8821	0.9236
Oriental	0.8398	0.7504	0.7952	0.6909	0.7263	0.7795
United	0.8441	0.7648	0.7547	0.7199	0.7787	0.8365

Source: Calculated by the author.

Table A2. Revenue efficiency scores for Model 2

Insurer	2012	2013	2014	2015	2016	2017
Bajaj Allianz	0.9160	0.9125	0.8754	0.8608	0.8175	0.8213
Cholamandalam	0.9450	0.9148	0.8534	0.8249	0.7877	0.8798
Future Generali	0.9390	0.9244	0.9113	0.8384	0.7799	0.6880
HDFC Ergo	0.7983	0.7430	0.8078	0.8180	0.7751	0.7981
ICICI Lombard	0.9063	0.8720	0.8041	0.8136	0.7010	0.6948
IFFCO Tokio	0.8257	0.8160	0.8679	0.9353	0.9230	0.8791
Reliance	0.6986	0.7414	0.8316	0.8395	0.7856	0.6286
Royal Sundaram	0.8736	0.8096	0.8432	0.8086	0.7683	0.8190
SBI General	0.3796	0.6810	0.7224	0.6881	0.5913	0.7396
Shri Ram General	0.9028	0.6100	0.7900	0.6998	0.6088	0.5613
Tata AIG	0.8510	0.8251	0.8427	0.8948	0.8815	0.8980
National	0.8637	0.7577	0.8344	0.8736	0.9000	0.8608
New India	0.8161	0.9179	0.8225	0.8165	0.8343	0.8150
Oriental	0.8611	0.8429	0.8189	0.7934	0.8498	0.8476
United	0.7379	0.7679	0.7751	0.7865	0.8243	0.8003

Source: Calculated by the author.

Table A3. Technical (revenue) inefficiency scores for Model 1

Insurer	2012	2013	2014	2015	2016	2017
Bajaj Allianz	0.3061	0.2379	0.1605	0.1045	0.1473	0.2031
Cholamandalam	0.0823	0.1107	0.1682	0.2188	0.3797	0.2799
Future Generali	0.1174	0.1062	0.1031	0.1642	0.2406	0.3564
HDFC Ergo	0.2626	0.3104	0.2298	0.3444	0.5305	0.4761
ICICI Lombard	0.1351	0.1325	0.2241	0.1934	0.4102	0.3157
IFFCO Tokio	0.1540	0.1962	0.1421	0.0678	0.0972	0.0787
Reliance	0.3329	0.2730	0.1810	0.1578	0.2221	0.2914
Royal Sundaram	0.1106	0.1643	0.0945	0.1207	0.1546	0.1501
SBI General	1.1982	0.5308	0.2848	0.2493	0.4823	0.2643
Shri Ram General	0.0692	0.3193	0.0615	0.0924	0.0978	0.0866
Tata AIG	0.1367	0.1446	0.1206	0.0760	0.1518	0.2152
National	0.1627	0.4017	0.1894	0.2700	0.2200	0.2192
New India	0.2163	0.0396	0.1681	0.1463	0.1255	0.0795
Oriental	0.1746	0.2871	0.2291	0.3698	0.3198	0.2491
United	0.1695	0.2681	0.2814	0.3286	0.2501	0.1785

Source: Calculated by the author.

Table A4. Technical (revenue) inefficiency scores for Model 2

Insurer	2012	2013	2014	2015	2016	2017
Bajaj Allianz	0.9160	0.9125	0.8754	0.8608	0.8175	0.8213
Cholamandalam	0.9450	0.9148	0.8534	0.8249	0.7877	0.8798
Future Generali	0.9390	0.9244	0.9113	0.8384	0.7799	0.6880
HDFC Ergo	0.7983	0.7430	0.8078	0.8180	0.7751	0.7981
ICICI Lombard	0.9063	0.8720	0.8041	0.8136	0.7010	0.6948
IFFCO Tokio	0.8257	0.8160	0.8679	0.9353	0.9230	0.8791
Reliance	0.6986	0.7414	0.8316	0.8395	0.7856	0.6286
Royal Sundaram	0.8736	0.8096	0.8432	0.8086	0.7683	0.8190
SBI General	0.3796	0.6810	0.7224	0.6881	0.5913	0.7396
Shri Ram General	0.9028	0.6100	0.7900	0.6998	0.6088	0.5613
Tata AIG	0.8510	0.8251	0.8427	0.8948	0.8815	0.8980
National	0.8637	0.7577	0.8344	0.8736	0.9000	0.8608
New India	0.8161	0.9179	0.8225	0.8165	0.8343	0.8150
Oriental	0.8611	0.8429	0.8189	0.7934	0.8498	0.8476
United	0.7379	0.7679	0.7751	0.7865	0.8243	0.8003

Source: Calculated by the author.