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# Efficiency of Indian General Insurance Companies: A Convex Nonparametric Least Squares Approach

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**Abstract.** In the current millennium, the Indian general insurance market has witnessed major structural changes because of the establishment of a market regulator and the initiation of entry deregulation. The present study evaluates the efficiency performance of fifteen Indian general insurance companies for the period 2011/12 - 2016/17 using a robust nonparametric approach. The study also seeks to explain efficiency by considering the influence of environmental variables on the efficiency scores. The results indicate that efficiency is positively related to ownership, insurer age, market share, and return on equity but negatively related to size.

**Keywords**: convex nonparametric regression, efficiency, general insurance, quantile regression

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## 1. Introduction

In view of the experiences derived from less developed countries, a significant section of policy makers argued in favor of dismantling total government control of the infrastructure and the financial services industries. A growing body of research literature has also provided support in favor of deregulation of these industries, as empirical evidence suggested that government-directed allocation of resources promoted misallocation of resources and provided undue benefits to certain groups of beneficiaries. Becker [6] provided a theoretical model of competition among political pressure groups that compete with each other for the directed allocation of benefits. Averch and Johnson [2] pointed out that the presence of regulatory control promotes inefficiency in operation and pricing by the service provider. The realization that both the entry and regulatory policies of the insurance market need to be reviewed led to the introduction of entry deregulation and prudential regulations for the insurance companies.

In the context of the Indian insurance sector, the general (non-life) insurance market was fully controlled by four public sector general insurance companies between 1973 and 1999. The absence of competition and the presence of tariff control in the industry resulted in distorted and slow growth for the sector and hindered product discovery. Following the implementation of the financial sector reform in India (since 1991), the government took steps to extend policy deregulation to the insurance sector as well. Based on the recommendations by the Indian General Insurance Sector, the industry experienced two crucial regulatory changes in 1999 (the

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establishment of the Insurance Regulatory and Development Authority as the market regulator and the deregulation of entry). The changes facilitated the growth of the number of private sector service providers in the market, and this in turn promoted scale and scope economies. The deregulation of private sector entry in the Indian general insurance sector in 1999 has resulted in a significant expansion of the industry in terms of size and product variety during the last two decades.

Given the developments in the general insurance sector, several research studies (e.g., [19, 28, 29]) have estimated the relative efficiency performance of Indian general insurance companies for the post-reform period using Data Envelopment Analysis (DEA), which is a non-parametric approach i.e., it does not assume any specific parametric relationship between the inputs and outputs of production. However, the DEA approach is incapable of capturing the statistical noise present in the relationship. Another limitation of the DEA approach is that the production frontier is constructed on the basis of a few influential observations and is quite sensitive to outliers. The present study seeks to remove the difficulties by adopting a stochastic DEA approach [25]. The approach used in the present study includes a stochastic noise term and estimates efficiency on the basis of the entire panel of observations. The study uses a two-stage approach. In the first stage, we have estimated insurer-wise efficiency for 15 general insurers for the period 2012/13 - 2017/18 (post-global financial crisis period). The adoption of a robust methodology of frontier estimation on panel data enables us to make an inter-temporal comparison of efficiency performance as efficiency is evaluated on the basis of a global frontier. In the second stage, we have regressed the efficiency scores estimated in the first stage on several environmental variables which influence efficiency performance indirectly. The paper includes five sections and proceeds in the following manner.

The paper is organized as follows. Section 2 gives an overview of the Indian general insurance industry. Section 3 provides a brief discussion of the related efficiency literature pertaining to both India and other countries. Section 4 discusses the methodology used in the present study, the competing estimation paradigms, and the data used. Section 5 presents and analyzes the results, while Section 6 concludes the paper.

## 2. General insurance industry in India

India had more than a hundred general insurance companies in operation at the time of its nationalization in 1972. The general insurance business was taken over by the government during this year by merging the existing private-sector general insurers. 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 (the National Insurance Company Limited, the New India Assurance Company Limited, the Oriental Insurance Company Limited, and the United India Insurance Company Limited). In 1991, India adopted LPG (liberalization, privatization, and globalization) policies with a greater role for the private sector in the economy. In the context of the Indian financial sector, reforms were first initiated in the banking sector, which involved deregulation of private sector entry and the introduction of prudential regulations for banking operations. In 1993, the Government of India set up a high-powered committee on the Indian insurance sector (headed by Shri R. N. Malhotra) for examining the existing insurance sector scenario and suggesting required measures for promoting competitive efficiency and framing a regulatory framework. The Committee submitted its report in 1994 and recommended that entry deregulation be introduced in both life and general insurance markets. Consequent on policy reform, newly established private insurers have been present in the general insurance market since their entry in 2000, and by end-March 2018, the total number of general insurance companies (including both diversified and stand-alone insurers) increased to 35. During the post-liberalization phase, the sector witnessed notable expansion in terms of various parameters like growth in gross and net premium collection, asset under management, number of offices of the insurance companies, insurance penetration (ratio of aggregate insurance premium to GDP) and insurance density (ratio of insurance premium to total population), and incurred claims ratio (ratio of total paid claims to total premium collected). Table 1 provides a brief overview of the growth statistics observed in the general insurance sector between end-March 2013 and end-March 2018.

| Particulars | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|
| Number of diversified general insurers | 21 | 21 | 21 | 22 | 21 | 25 |
| Insurance Penetration | 0.8 | 0.7 | 0.7 | 0.77 | 0.93 | 0.97 |
| Insurance Density (in USD) | 11 | 11 | 12 | 13.2 | 18 | 19 |
| Number of offices | 8,099 | 9,872 | 10,407 | 10,803 | 11,141 | 11,200 |
| Number of New Policies Issued (in 000) | 107,000 | 104,800 | 120,200 | 125,700 | 152,500 | 158,485 |
| Gross Direct Premium (in 000 Rs) | 650,230 | 799,340 | 871,510 | 993,330 | 1,309,710 | 1,534,377 |
| Asset Under Management (in 000 Rs) | 1,229,920 | 1,495,360 | 1,721,440 | 1,881,260 | 2,223,440 | 2,689,288 |
| Incurred claims ratio | 82.8 | 76.5 | 73.6 | 74.4 | 84.4 | 85.26 |

Table 1: *The general insurance industry in India - an overview.*
*Souce:* IRDA: Handbook of Insurance Statistics, various years.

## 3. Review of the related literature

Several research studies estimated the efficiency and total factor productivity of non-life insurance companies in the international context. Some of the studies inquired about the impact of environmental variables on efficiency or productivity. Fukuyama and Weber [18] estimated the technical efficiency and Malmquist index of total factor productivity growth of Japanese non-life insurance companies for the period 1983–1994. The study found that significant productivity improvements (induced by technological change) took place during 1983–1990. Ennsfellner *et al.* [14] made efficiency evaluations of Austrian insurance companies for 1994–1999 using a Bayesian stochastic frontier. The study found that the process of deregulation of the Austrian insurance market had positively influenced the productive efficiency of the observed insurers. Barros *et al.* [4] estimated the efficiency and productivity of Portuguese insurance companies for the period 1995–2001 and found efficiency and productivity performance variations across insurers caused by a variety of influencing factors, such as asymmetrical distribution of market information across companies leading to the prevalence of incomplete insurance markets, differences in the scale and scope economies among the competing insurers, etc.

Kao and Hwang [21] applied both relational and independent two-stage DEA models for estimating the marketing and investment performance of 24 Taiwanese non-life insurance companies. The study showed that investment efficiency was lower than marketing efficiency. Cummins and Xie [10] examined the impact of business consolidations in the US property-liability insurance industry on the productivity and efficiency of the insurers based on data from 1994-2003. The results suggested that mergers and acquisitions in property-liability insurance improved the valuation of the concerned insurers. The acquiring insurers achieved more revenue efficiency gains than non-acquiring companies. Barros *et al.* [5] 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 are 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, the degree of competition was not enough to improve market efficiency during the period. Cummins and Xie [11] examined efficiency, productivity, and scale economies in the U.S. property-liability insurance industry. The study analyzed efficiency and changes in total factor productivity using data envelopment analysis. The results showed that the majority of the insurers below the median size in the industry exhibited increasing returns to scale, and the majority of the insurers above the median size exhibit decreasing returns to scale. Alhassan and Biekpe [1] evaluated the efficiency, productivity, and returns to scale of South African non-life insurance companies for 2007–2012. For efficiency evaluation, the study employed data envelopment analysis and, for second stage regression, truncated bootstrapped and logistic regression techniques for identifying the determinants of efficiency were applied. 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 this 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.

Biener *et al.* [8] estimated the efficiency and productivity of Swiss life, property-casualty, and other insurance companies for the period 1997–2013 using a bootstrap DEA approach. The study found that during the period under observation, efficiency and productivity improved in the property-casualty and reinsurance businesses.

Ferro and León [17] applied stochastic frontier analysis 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 a 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.

In the Indian context, there are recent studies considering this topic [19, 28, 29]. Ilyas and Rajasekharan [19] estimated the efficiency and total factor productivity of the general insurance industry of India for the period 2005–2016. Sinha [28] estimated the efficiency performance of the Indian general insurance sector using the conditional performance benchmarking approach. The author has also estimated the two-stage network efficiency of Indian general insurers [29].

The existing literature on non-life insurance efficiency and productivity estimation uses either a parametric stochastic frontier model or a purely non-parametric approach with no statistical interpretation of results. The objective of the present study is to adopt a unified approach for the estimation of insurer performance.

## 4. Methodology of estimation and data

### 4.1. Estimation of the efficiency frontier

In general, there are two competing approaches for estimating the efficiency performance of decision-making units: data envelopment analysis (DEA), a non-parametric approach (no parametric specification of the relationship between the inputs and outputs is required), and stochastic frontier analysis (SFA), an econometric approach. The DEA approach ([9] and [3]) is based on the conceptual and empirical foundations provided by Shephard [27] and Farrell [16]. Efficiency evaluation of the decision-making units using DEA is based on the assumptions of free disposability of inputs and outputs, convexity of technology, and returns to scale. The DEA approach is, however, deterministic and is not capable of accommodating statistical noise. In the SFA approach, the deviations from the frontier are decomposed into a one-sided (non-negative) component (representing firm inefficiency) and a random component accounting for measurement inaccuracies and other random noise. However, a limitation of the SFA approach is the requirement for a priori specification of a parametric relationship between the inputs and the output. While flexible functional forms are also often used in the context of SFA, such forms are often incompatible with the monotonicity, convexity, and homogeneity conditions.

More recent developments in the context of frontier estimation using stochastic frontier analysis have attempted to get rid of the parametric specification through the application of non-parametric regression. Kneip and Simar [22] introduced a general framework for the estimation of a frontier model in the context of panel data. The study proposed a non-parametric estimation methodology for individual production functions. Fan *et al.* [15] introduced a semi-parametric production frontier model in which the functional form of the production frontier is unspecified and the distribution of the composed error terms is of known form. In their approach, the frontier is estimated by using kernel regression, and the conditional expected inefficiency is estimated on the basis of the composite error term, which includes a two-sided statistical noise and a one-sided error term representing technical inefficiency. Kumbhakar *et al.* [24] proposed a stochastic frontier model based on local maximum likelihood techniques. Their model extended the proposed approach by considering order-m local polynomial estimators and using local estimates of the parametric components of the model.

In the present study, we have applied the two-stage frontier estimation approach introduced by Kuosmanen and Kortelainen [25]. In the first stage of this approach, the shape of the frontier is estimated by a convex nonparametric least squares approach, which satisfies monotonicity and convexity. In the second stage, the variance parameters and the conditional expectations of inefficiency are estimated using the method of moments approach. The method is now discussed in brief.

Let us consider an $m$ input single output technology $Y = f(X)$ where $X = 1, 2, 3, ..., m$ represents the input vector and y represents the output vector. The frontier production function indicates the maximum output which can be produced from the given quantities of the $m$ inputs. However, the observed output $Y_i$ of firm $i$ can deviate from $f(X_i)$ due to the presence of inefficiency and noise. Thus, the observed output and the frontier output may be related in the following manner:

$$Y_i = f(X_i) + e_o = f(X_i) - u_i + v_i \tag{1}$$

Here $u_i$ represents inefficiency and $v_i$ represents the random noise. $u_i$ and $v_i$ are independent of each other and of the $m$ inputs. Furthermore, $E(u_i) = \mu(> 0)$ and $E(\mu_i - \mu)^2 = {\sigma_u}^2$. On the other hand, $E(v_i) = 0$ and $E(v_i - 0)^2 = {\sigma_v}^2$. The deterministic part of the technology is assumed to be continuous, monotonic, and globally concave.

For the application of CNLS approach in the first stage, it is essential to rearrange (1) in the following manner:

$$Y_i = [f(X_i) - u_i] + v_i = g(X_i) + v_i \tag{2}$$

where $g(X_i)$ represents the average production function instead of the frontier production function. The CNLS estimate of $g(X_i)$ is obtained as

$$min \sum_{i=1}^{n} [Y_i - g(X_i)]^2 = min \sum_{i=1}^{n} v_i^2 \tag{3}$$

where $g(X_i)$ is a monotonic increasing and concave function.

The second stage of the estimation process requires estimation of second and third order central moments which enables the computation of the variances of inefficiency and random noise terms. Given that the inefficiency term follows a half normal distribution and the random noise term follows standard normal distribution, we can relate the second and third order central moments with the variance terms as:

$$M_2 = \left[\frac{\pi - 2}{\pi}\right]\sigma_u^2 + \sigma_v^2 \tag{4}$$

$$M_3 = \left(\sqrt{\frac{\pi - 2}{\pi}}\right)\left[1 - \frac{4}{\pi}\right]\sigma_u^3 \tag{5}$$

For the CNLS approach, we can estimate the second and third order central moments:

$$\widehat{M_2} = \frac{1}{n}\sum_{i=1}^{n}(\widehat{v_i} - E(v_i))^2 \tag{6}$$

$$\widehat{M_3} = \frac{1}{n}\sum_{i=1}^{n}(\widehat{v_i} - E(v_i))^3 \tag{7}$$

The standard deviation of inefficiency $\widehat{\sigma_u}$ and random noise term $\widehat{\sigma_v}$ can be estimated from equations (4) thorugh (7).

## 4.2. Influence of environmental variables

It is critical to consider the influence of environmental variables on estimated efficiencies when explaining the efficiency performance of observed productive units. In most of the research studies, the second-stage analysis (for estimating the influence of environmental variables) uses either pooled ordinary least squares or censored regression. However, if the data set has outliers and is not normally distributed, then ordinal least squares give biased estimates. Further efficiency data is not censored. In view of this, quantile regression, introduced by Koenker and Bassett [23] is applied in the second stage of the current study as it provides a robust estimate of the regression relation. In order to briefly explain of the methodology of quantile regression, let us consider a regression model

$$Y = \beta X + e \tag{8}$$

where $Y$ stands for the dependent variable and $X$ represents the vector of explanatory variables. On the other hand, $\beta$ represents the coefficients subject to estimation and $e$ stands for the white noise error. In the least squares method, the sum of squares of deviations is minimized:

$$min\sum_{i=1}^{n}(Y_i - \widehat{Y})^2 \tag{9}$$

In the quantile regression approach, one minimizes the weighted total of positive and negative deviations of the estimates from the observed values $min[\Psi(Y_U - X\hat{\beta}) + (1 - \Psi)(X\hat{\beta} - Y_L)]$, where $Y_U$ includes all such values of $Y$ which are greater than $X\hat{\beta}$ and $Y_L$ represents those values of $Y$ which are less than $X\hat{\beta}$. $\Psi$ portrays the quantile level.

### 4.3. Description of variables and data

Estimation of efficiency based on a stochastic frontier requires the identification of inputs and outputs. However, the specification of inputs and outputs in the context of the insurance industry depends on the perspective from which the frontier is estimated. Erling and Luhnen [13] pointed out that the following three types of inputs are mainly used in the insurance industry: labor (office employees and agents), business services, and capital (debt and equity capital). On the output side, Leverty and Grace [26] 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 (who are 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 as outputs those activities that give significant value, assessed using operating cost allocations [7]. 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 ([12] and [20]) used net premiums as value added, while Ennsfellner *et al.* [14] used incurred benefits and the changes in reserves as output proxies.

The present study seeks to construct an income frontier. Therefore, we need to identify the major activities that contribute to insurer revenue. In the absence of very detailed information on various inputs separately, we have considered two inputs: total operating expenses and investments. The first input is used as a proxy to capture operational activities that are required to generate premium. The second input captures the investment activities of general insurance companies. On the output side, we have considered net premium income and income from investments as the two outputs. For the second stage analysis (linkage of efficiency with environmental variables), we have considered an ownership indicator (a dummy variable that is 0 for public sector general insurers and 1 for private sector general insurers), insurer age (in years), insurer size (log of total asset), market share (in terms of gross direct premium collected), and return on equity. Table 2 provides an overview of inputs and outputs and environmental variables.

| Description | Input/Output |
|---|---|
| Operating expenses | Input |
| Investments | Input |
| Total income = Net Premium Income + Investment Income | Output |
| Ownership, Insurer Age, Insurer Size, Market Share, and Return on Equity (ROE) | Environmental variables |

Table 2: *Inputs, outputs, and environmental variables.*

The period of the present study is 2012/13 - 2017/18. For the current study, we have collected data relating to the input, output, and environmental variables from the IRDA annual reports and the IRDA Handbook on Indian Insurance Statistics for the relevant years.

## 5. Results and analysis

### 5.1. Frontier related results

Table 3 provides the mean values of the regression coefficients observed for the in-sample years. $\beta_1$ denotes the coefficient of input 1 (operating expenses) and $\beta_2$ represents the coefficient of input 2 (investments). The insurer-wise coefficients for the observed years are included in appendix tables A-1 through A-6.

Our model is robust as a global benchmark has been and was constructed based on the entire panel data. Consequently, the efficiency scores are intertemporally comparable. Through appropriate normalization, the problem of heteroskedasticity has been taken care of. Table 4 presents the descriptive statistics (mean, standard deviation, skewness, and kurtosis) of the efficiency scores for the observed time period (2011/12 - 2016/17). The insurer-wise efficiency scores are presented in appendix table A-7. Please note that due to the presence of two-sided random noise $v$ in the model, efficiency scores can be greater than 1 in some cases. This is because $v_i > 0$ and $|v_i| > |u_i|$, we have $Y_i > f(X_i)$.

| Coefficient | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|
| Intercept | 1.6407 | 2.2767 | 2.4830 | 2.6047 | 2.8320 | 2.8623 |
| $\beta_1$ | 0.2147 | 0.3185 | 0.3005 | 0.2942 | 0.2677 | 0.3435 |
| $\beta_2$ | 0.7682 | 0.5896 | 0.5734 | 0.5729 | 0.5612 | 0.4866 |

Table 3: *Mean values of coefficients.*
*Souce:* Authors' calculations.

Table 4 shows that during the period under consideration, the mean efficiency score varied between 95.06% and 97.67%. Between 2013/14 and 2017/18, there has been secular improvement in the mean efficiency. Variability in efficiency has declined during the same period, which can be seen in the movement in the standard deviation of efficiency scores. Apart from the period 2015/16, efficiency distribution has exhibited negative skewness, indicating a long left tail of efficiency distribution. Kurtosis was highest for 2014/15 and lowest for 2012/13. It is evident that since 2014/15, the peak of efficiency distribution has declined over the years.

| Particulars | 2012/13 | 2013/14 | 2014/15 | 2015/16 | 2016/17 | 2017/18 |
|---|---|---|---|---|---|---|
| Mean efficiency | 0.9506 | 0.9498 | 0.9580 | 0.9655 | 0.9651 | 0.9767 |
| Standard deviation | 0.0396 | 0.0407 | 0.0349 | 0.0296 | 0.0249 | 0.0237 |
| Skewness | -1.3308 | -1.6904 | -0.4793 | 0.0579 | -0.0346 | -0.2728 |
| Kurtosis | 0.3846 | 3.7559 | 4.1530 | 1.8889 | 2.4792 | 2.1678 |

Table 4: *Descriptive statistics of efficiency scores.*
*Souce:* Authors' calculations.

### 5.2. Relationship of efficiency with environmental variables

In the present study, we have used quantile regression for estimating the relationship of the log of efficiency with the selected environmental variables (ownership indicator, insurer age, market share of the observed insurance companies, insurer size, and return on equity). We used a 16-section dummy to control insurer-specific factors. The ownership indicator is 0 for public sector insurers and 1 for the private sector. Insurer age is expressed in the number of completed years. A log of total assets is taken as the proxy of size. We have considered three quantiles

(0.25, 0.50, and 0.75) for the purpose of estimation. Theoretically, private ownership, market share, age, and return on equity should positively influence efficiency. The linkage between efficiency and insurer size, however, depends on whether economies or diseconomies of scale are present. The presence of economies of scale should positively influence efficiency. On the other hand, the linkage between efficiency and insurer size will be negative if diseconomies of scale are present.

The regression results are presented in Table 5 and Table 6. Table 5 provides the estimates of the coefficients for the explanatory variables, standard errors of the coefficient estimates, and the observed t ratios. The estimated relationships indicate that efficiency is positively related to ownership dummy, insurer age, market share, and return on equity but negatively related to size. For all selected quantile levels (0.25, 0.5, and 0.75), the coefficients of ownership, age, market share, and size are significant at the 95% level. The coefficient of return on equity is significant (at 95% level of confidence) for quantile levels of 0.25 and 0.5.

| Variables | Quantile | Coefficient | Standard Error | Observed t-ratio |
|---|---|---|---|---|
| *Intercept* | 0.25 | -0.2077 | 0.0259 | -8.012 |
| | 0.50 | -0.1404 | 0.0326 | -4.310 |
| | 0.75 | -0.0956 | 0.0372 | -2.566 |
| *Ownership Dummy* | 0.25 | 0.1587 | 0.0150 | 10.56 |
| | 0.50 | 0.1087 | 0.0189 | 5.761 |
| | 0.75 | 0.0855 | 0.0216 | 3.960 |
| *Return on Equity (ROE)* | 0.25 | 0.0970 | 0.0151 | 6.427 |
| | 0.50 | 0.1237 | 0.0190 | 6.521 |
| | 0.75 | 0.0732 | 0.0217 | 3.375 |
| *Log of Total Assets* | 0.25 | -0.0141 | 0.0034 | -4.107 |
| | 0.50 | -0.0119 | 0.0043 | -2.763 |
| | 0.75 | -0.0105 | 0.0049 | -2.137 |
| *Market Share* | 0.25 | 0.4042 | 0.0825 | 4.901 |
| | 0.50 | 0.2502 | 0.1036 | 2.415 |
| | 0.75 | 0.1422 | 0.1185 | 1.201 |
| *Insurer Age* | 0.25 | 0.0056 | 0.0005 | 12.08 |
| | 0.50 | 0.0042 | 0.0006 | 7.192 |
| | 0.75 | 0.0035 | 0.0007 | 5.227 |

Table 5: *Quantile regression of log of efficiency scores on environmental variables.*
*Souce:* Authors' calculations.

Table 6 provides the estimates for the regression residuals. The sum of absolute residuals and sum of squared residuals improved for the 50 percent quantile but deteriorated for the 75 percent quantile.

| Sum of absolute residual | | Sum of squared residual | |
|---|---|---|---|
| *Quantile* | *Value* | *Quantile* | *Value* |
| 0.25 | 1.7446 | 0.25 | 0.0596 |
| 0.5 | 1.424 | 0.5 | 0.0416 |
| 0.75 | 1.7606 | 0.75 | 0.0639 |

Table 6: *Regression residuals.*
*Souce:* Authors' calculations.

## 6. Conclusion

This study follows a two-stage approach for insurance efficiency evaluation and exploration of the impact of determinants of efficiency. In the first stage, it evaluates the efficiency of Indian general insurers. In the second stage, it seeks to explain efficiency by regressing efficiency scores on environmental variables (insurer age, market share, insurer size, and return on equity), which influence insurer performance. However, our approach is different from the methods used in the extant literature for both the first and second stages. In the first stage (in which efficiency is evaluated), we used the convex nonparametric least squares. In the second stage, in order to provide robust regression estimates, we used quantile regression instead of the mean-based least squares approach. The results indicate that private insurer ownership has a positive influence on efficiency performance. Furthermore, experience (age) also has a positive impact on efficiency. The role of market share and profitability (return on equity) is also positive and significant. However, the negative relationship between efficiency and insurer size is (perhaps) indicative of diseconomies of scale. Overall, the second stage results are in conformity with [28], although the current study includes many more environmental variables. The second-stage results enable us to assess the importance of the environmental variables on insurer efficiency.

The study, however, has two weaknesses. First, the sample size could be increased by including more insurance firms – however, this would make the panel unbalanced. Second, the period of analysis could also be extended to provide more insight about the sector's performance. We expect that future studies will take care of that issue.

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## Appendices

### A1. Frontier Regression estimates for 2012/13.

| Insurance Company | Intercept | $\beta_1$ | $\beta_2$ |
|---|---|---|---|
| Bajaj Allianz | 1.4575 | 0.2026 | 0.7899 |
| Bharti Axa | 1.4575 | 0.2026 | 0.7899 |
| Cholamandalam | 0.1588 | 0.2113 | 0.9953 |
| Future Generali | 1.4575 | 0.2026 | 0.7899 |
| HDFC Ergo | 1.4575 | 0.2026 | 0.7899 |
| ICICI Lombard | 1.4575 | 0.2026 | 0.7899 |
| IFFCO Tokio | 1.4575 | 0.2026 | 0.7899 |
| Reliance General | 3.0524 | 0.3238 | 0.4718 |
| Royal Sundaram | 0.2573 | 0.1012 | 1.0842 |
| SBI General | 1.4575 | 0.2026 | 0.7899 |
| Shri Ram General | 0.1017 | 0.3741 | 0.8743 |
| Tata AIG | 1.4575 | 0.2026 | 0.7899 |
| National Insurance | 1.3779 | 0.0819 | 0.9199 |
| New India Assurance | 4.2721 | 0.5192 | 0.1591 |
| Oriental Insurance | 1.4575 | 0.2026 | 0.7899 |
| United India | 3.9130 | 0.0000 | 0.6774 |

*Souce:* Authors' calculations.

### A2. Frontier Regression estimates for 2013/14.

| Insurance Company | Intercept | $\beta_1$ | $\beta_2$ |
|---|---|---|---|
| Bajaj Allianz | 1.4575 | 0.2026 | 0.7899 |
| Bharti Axa | 1.4575 | 0.2026 | 0.7899 |
| Cholamandalam | 1.4575 | 0.2026 | 0.7899 |
| Future Generali | 1.4575 | 0.2026 | 0.7899 |
| HDFC Ergo | 1.4575 | 0.2026 | 0.7899 |
| ICICI Lombard | 3.0524 | 0.3238 | 0.4718 |
| IFFCO Tokio | 1.4575 | 0.2026 | 0.7899 |
| Reliance General | 3.0524 | 0.3238 | 0.4718 |
| Royal Sundaram | 1.4575 | 0.2026 | 0.7899 |
| SBI General | 1.4575 | 0.2026 | 0.7899 |
| Shri Ram General | 0.1155 | 0.5474 | 0.7447 |
| Tata AIG | 1.4575 | 0.2026 | 0.7899 |
| National Insurance | 4.2721 | 0.5192 | 0.1591 |
| New India Assurance | 4.2721 | 0.5192 | 0.1591 |
| Oriental Insurance | 4.2721 | 0.5192 | 0.1591 |
| United India | 4.2721 | 0.5192 | 0.1591 |

*Souce:* Authors' calculations.

## A3. Frontier Regression estimates for 2014/15.

| Insurance Company | Intercept | $\beta_1$ | $\beta_2$ |
|---|---|---|---|
| Bajaj Allianz | 3.0524 | 0.3238 | 0.4718 |
| Bharti Axa | 1.4575 | 0.2026 | 0.7899 |
| Cholamandalam | 1.4575 | 0.2026 | 0.7899 |
| Future Generali | 1.4575 | 0.2026 | 0.7899 |
| HDFC Ergo | 1.4575 | 0.2026 | 0.7899 |
| ICICI Lombard | 3.0524 | 0.3238 | 0.4718 |
| IFFCO Tokio | 1.4575 | 0.2026 | 0.7899 |
| Reliance General | 3.0524 | 0.3238 | 0.4718 |
| Royal Sundaram | 1.4575 | 0.2026 | 0.7899 |
| SBI General | 1.4575 | 0.2026 | 0.7899 |
| Shri Ram General | 1.4575 | 0.2026 | 0.7899 |
| Tata AIG | 1.4575 | 0.2026 | 0.7899 |
| National Insurance | 4.6366 | 0.4555 | 0.1735 |
| New India Assurance | 4.2721 | 0.5192 | 0.1591 |
| Oriental Insurance | 4.2721 | 0.5192 | 0.1591 |
| United India | 4.2721 | 0.5192 | 0.1591 |

*Souce:* Authors' calculations.

## A4. Frontier Regression estimates for 2015/16.

| Insurance Company | Intercept | $\beta_1$ | $\beta_2$ |
|---|---|---|---|
| Bajaj Allianz | 3.0524 | 0.3238 | 0.4718 |
| Bharti Axa | 3.0524 | 0.3238 | 0.4718 |
| Cholamandalam | 1.4575 | 0.2026 | 0.7899 |
| Future Generali | 1.4575 | 0.2026 | 0.7899 |
| HDFC Ergo | 1.4575 | 0.2026 | 0.7899 |
| ICICI Lombard | 3.0524 | 0.3238 | 0.4718 |
| IFFCO Tokio | 1.4575 | 0.2026 | 0.7899 |
| Reliance General | 1.4575 | 0.2026 | 0.7899 |
| Royal Sundaram | 1.4575 | 0.2026 | 0.7899 |
| SBI General | 1.4575 | 0.2026 | 0.7899 |
| Shri Ram General | 0.1435 | 0.6208 | 0.6864 |
| Tata AIG | 1.4575 | 0.2026 | 0.7899 |
| National Insurance | 7.5332 | 0.0000 | 0.2532 |
| New India Assurance | 4.2721 | 0.5192 | 0.1591 |
| Oriental Insurance | 4.2721 | 0.5192 | 0.1591 |
| United India | 4.6366 | 0.4555 | 0.1735 |

*Souce:* Authors' calculations.

## A5. Frontier Regression estimates for 2016/17.

| Insurance Company | Intercept | $\beta_1$ | $\beta_2$ |
|---|---|---|---|
| Bajaj Allianz | 3.0524 | 0.3238 | 0.4718 |
| Bharti Axa | 3.0524 | 0.3238 | 0.4718 |
| Cholamandalam | 1.4575 | 0.2026 | 0.7899 |
| Future Generali | 1.4575 | 0.2026 | 0.7899 |
| HDFC Ergo | 1.4575 | 0.2026 | 0.7899 |
| ICICI Lombard | 3.0524 | 0.3238 | 0.4718 |
| IFFCO Tokio | 1.4575 | 0.2026 | 0.7899 |
| Reliance General | 1.4575 | 0.2026 | 0.7899 |
| Royal Sundaram | 1.4575 | 0.2026 | 0.7899 |
| SBI General | 1.4575 | 0.2026 | 0.7899 |
| Shri Ram General | 3.0524 | 0.3238 | 0.4718 |
| Tata AIG | 1.4575 | 0.2026 | 0.7899 |
| National Insurance | 7.5332 | 0.0000 | 0.2532 |
| New India Assurance | 4.6366 | 0.4555 | 0.1735 |
| Oriental Insurance | 4.6366 | 0.4555 | 0.1735 |
| United India | 4.6366 | 0.4555 | 0.1735 |

*Souce:* Authors' calculations.

## A6. Frontier Regression estimates for 2017/18.

| Insurance Company | Intercept | $\beta_1$ | $\beta_2$ |
|---|---|---|---|
| Bajaj Allianz | 4.2721 | 0.5192 | 0.1591 |
| Bharti Axa | 4.2721 | 0.5192 | 0.1591 |
| Cholamandalam | 1.4575 | 0.2026 | 0.7899 |
| Future Generali | 1.4575 | 0.2026 | 0.7899 |
| HDFC Ergo | 3.0524 | 0.3238 | 0.4718 |
| ICICI Lombard | 3.4819 | 0.3894 | 0.3641 |
| IFFCO Tokio | 3.0524 | 0.3238 | 0.4718 |
| Reliance General | 1.4575 | 0.2026 | 0.7899 |
| Royal Sundaram | 1.4575 | 0.2026 | 0.7899 |
| SBI General | 1.4575 | 0.2026 | 0.7899 |
| Shri Ram General | 3.0524 | 0.3238 | 0.4718 |
| Tata AIG | 1.4575 | 0.2026 | 0.7899 |
| National Insurance | 3.0524 | 0.3238 | 0.4718 |
| New India Assurance | 4.2721 | 0.5192 | 0.1591 |
| Oriental Insurance | 4.2721 | 0.5192 | 0.1591 |
| United India | 4.2721 | 0.5192 | 0.1591 |

*Souce:* Authors' calculations.

## A7. Insurer wise efficiency scores for the in-sample years.

| Insurance Company | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|
| Bajaj Allianz | 0.9793 | 0.9744 | 0.9670 | 0.9721 | 0.9654 | 0.9824 |
| Bharti Axa | 0.8718 | 0.8336 | 0.8659 | 0.9014 | 0.9075 | 0.9194 |
| Cholamandalam | 0.9586 | 0.9649 | 0.9777 | 0.9837 | 0.9780 | 0.9815 |
| Future Generali | 0.8916 | 0.9073 | 0.9345 | 0.9369 | 0.9426 | 0.9630 |
| HDFC Ergo | 0.9543 | 0.9595 | 0.9614 | 0.9678 | 0.9572 | 0.9728 |
| ICICI Lombard | 0.9705 | 0.9716 | 0.9661 | 0.9729 | 0.9717 | 0.9807 |
| IFFCO Tokio | 0.9794 | 0.9709 | 0.9712 | 0.9698 | 0.9715 | 0.9772 |
| Reliance General | 0.9212 | 0.9344 | 0.9543 | 0.9912 | 0.9837 | 0.9913 |
| Royal Sundaram | 0.9718 | 0.9698 | 0.9743 | 0.9794 | 0.9741 | 0.9691 |
| SBI General | 0.8691 | 0.9001 | 0.9290 | 0.9340 | 0.9501 | 0.9637 |
| Shri Ram General | 0.9853 | 1.0092 | 1.0393 | 1.0350 | 1.0238 | 1.0272 |
| Tata AIG | 0.9603 | 0.9601 | 0.9554 | 0.9593 | 0.9547 | 0.9653 |
| National Insurance | 0.9866 | 0.9567 | 0.9511 | 0.9596 | 0.9661 | 0.9840 |
| New India Assurance | 0.9703 | 0.9669 | 0.9721 | 0.9759 | 0.9757 | 0.9909 |
| Oriental Insurance | 0.9723 | 0.9440 | 0.9382 | 0.9360 | 0.9398 | 0.9520 |
| United India | 0.9666 | 0.9741 | 0.9701 | 0.9730 | 0.9791 | 1.0064 |

*Souce:* Authors' calculations.