Dynamic Productivity Analysis of Insurance Firms - The Effect of Firm-Specific and Macroeconomic Characteristics

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Abstract: This study measures dynamic productivity for life and non-life insurance firms and investigates the effects of firm-specific and macroeconomic factors on productivity. The empirical estimation uses an eight-year panel of data ending in 2016 for 14 life and 18 non-life firms operating in India. Using data envelopment analysis (DEA), the study estimates Malmquist productivity indexes and finds that total factor productivity for life insurers decreased by 11.8 percent and for non-life insurers by 0.4 percent during the study period. Tobit regression analysis found distribution ratio, claims ratio, and input cost ratio have generally similar effects for life and non-life firms in terms of their significance and direction of change. Macroeconomic variables have the expected sign and significant effect for life insurance firms but no effect for non-life firms. The study suggests insurance firms in India need to improve their operating performance, lower combined ratios, and focus on redesigning channel strategy for product and service distribution, while raising financial awareness of customers. The current study contributes to the body of the existing literature on firm productivity providing valuable information about factors that influence dynamic productivity of insurance firms. The results will benefit consumers and firm managers, as well as regulatory authorities seeking to make informed decisions for policy implementation.

Keyword: Productivity, Efficiency, Life Insurance, Non-life Insurance, Regression, DEA

JEL Classification: G14, G22, C14

1. Introduction

A well-functioning insurance sector plays a significant role in economic development of any nation in the modern world. It helps protect institutions from unforeseen losses, smoothing earnings of businesses and generating value for both policyholders and shareholders, while enabling increases in national investment and providing jobs and earnings for its distributors. Over the last sixteen years, privatization, liberalization, and deregulation in Indian insurance markets have caused huge changes in competition, business environment, quality of services, new product development, new delivery channels (i.e., bancassurance), brokers and direct selling through the internet, and greater use of information technology. With rapid economic growth, and rising middle class population and wealth, India witnessed a 23 percent increase in first year premiums for life insurance between 2002 and 2011 and a 16 percent increase in non-life gross direct premiums between 2002 and 2015 (IRDA, 2014). Compared to slow growth for insurance premiums in developed countries, growth in emerging markets for 2016-17 is expected to be around 10.7 percent for life and 8.3 percent for non-life. India is one of the strongest nations in the emerging market, having registered a growth in premium of 7.8 percent for life and 8.1percent for non-life insurance in 2015 (SwissRe 2016). The high growth potential for insurance markets in India, coupled with a new government regulation in 2015 that raised the foreign joint venture companies' investment cap from 26 to 49 percent with the safeguard of Indian ownership and control, has created an unique opportunity for foreign domestic investment.

However, compared to other nations in the emerging market and comparable Asian nations, insurance density and penetration in India is among the lowest in Asia (Table 1), although India has the highest GDP growth among all nations in 2015. While China was the major force for the growth of insurance business among the BRICS nations in 2013-14, India will likely set the stage for growth and investment in insurance business for 2015-20 (SwissRe, 2016). In a highly competitive insurance market, one of the major areas of focus for various stakeholders i.e., policyholders, agents, and policy makers, is the financial performance of the firms. Financial performance is generally measured by profitability, because profits attract investors, improve the level of solvency, and strengthen policyholder confidence. Financial performance of an insurance firm depends on the efficiency and productivity gains achieved in the process of delivering its services. Further, an insurer's profit is also influenced by the operational efficiency, technical reserve, equity capital, and investments, including firm specific and macroeconomic characteristics (Dumpos et al. 2012).

Compared to the number of studies devoted to profitability and productivity analysis for banking sector, there are relatively few studies of the Indian insurance sector. Most of the studies using Indian insurance market data analyzed either static cost or productive efficiency for life or non-life insurance firms (Sinha, 2007; Shina et al. 2011; Tone et al. 2005; Chakraborty et al. 2012 and 2013; and Joo 2013). Some studies measured dynamic productivity for non-life insurance firms (Chakraborty et al. 2013) and life insurance firms (Sinha 2015) using relatively short panels of data. There are no studies to our knowledge that have measured dynamic productivity and its components using a long panel of data for both life and non-life insurance firms from India and explored the effect of firm-specific and macroeconomic factors on productivity change. Two main objectives for this study are: (1) to estimate the dynamic productivity indexes for life and non-life insurance firms using an 8-year panel of data; and (2) to identify the effect of firm-specific and macroeconomic characteristics on the components of productivity indexes.

In order to achieve the first objective we use input-oriented DEA model estimated Malmquist productivity indexes i.e., efficiency change (EFFCH), technological change (TECHCH), and total factor productivity change (TFPCH). To achieve the second objective we employ a truncated regression in which firm-specific characteristics and macroeconomic variables are regressed on EFFCH, TECHCH, and TFPCH. There are two main contributions of this paper to the existing literature. First, this study uses a larger and more recent set of panel data and includes both life and non-life firms and measured dynamic productivity indexes. Second, the differences in the dynamic productivity index among firms are explored using sound econometric methodology. The results from this study provide important information for business managers in formulating operational strategy and for policy makers in making informed decisions affecting the competitive environment. The remainder of the paper is organized as follows. The next section offers a brief overview of the literature and is followed by a section describing the dataset used for this study.

The third section defines the methodology implemented and the fourth section discusses the empirical results. Conclusions and comments are provided in the final section.

2. Overview of the Literature

Frontier efficiency methodology that benchmarks firm performance relative to 'best practice' frontiers used by the leading firms in the industry has become a standard method for efficiency analysis in the insurance industry. Eling and Luhnen (2010) surveyed 95 studies reporting efficiency measures for firms in the insurance industry and found that 55 of those studies used DEA. A limited number of studies have been devoted to exploring the efficiency and productivity of the Indian insurance firms in the era of deregulation. (Rodrik and Subramanian 2003; Guerrero and Singh 2004; Sinha 2004; Tone and Sahoo 2005; Singh 2005; Sinha and Chatterjee 2009; Chakraborty et al. 2012 and 2013; Sinha 2015). Tone and Sahoo (2005) undertook the first empirical study analyzing the cost efficiency of the state-owned Life Insurance Company of India (LIC) using a modified version of data envelopment analysis. The authors recognized that a small sample size and brief study period limited the robustness of their study and recommended that future research on the topic use data on multiple firms for multiple years during the deregulation era. Sinha (2004) estimated technical efficiency for four state-owned non-life insurers using seven years (1997-2003) of data and applied DEA methods. The authors found that the relative efficiency levels for three firms converged toward the terminal level while one firm (New India Assurance Co.) maintained the highest efficiency for all years. Sinha (2007) estimated technical efficiency and total factor productivity of 13 life insurers using three years of data (2003-05) and found that the total factor productivity growth for private firms was higher than for the government-owned LIC. Sinha and Chatterjee (2009) estimated the cost efficiency of 13 life insurers using four years of data and applied the DEA method. They found that except for the state-owned LIC, overall efficiency for all firms increased during the first two years but then reversed during the last two years.

Chakraborty et al. (2013) used parametric and non-parametric methods and analyzed the performance of non-life insurance firms. The study found that the efficiency scores are sensitive to the estimation methods used and that most of the firms achieved gains in total factor productivity over time. Sinha (2015) used seven years of panel data for life insurance firms and estimated dynamic slack-based DEA efficiency and found technical efficiencies are generally low, and that there were significant fluctuations in mean technical efficiency over the study period. It is well-recognized in the DEA literature that the efficiency measure is sensitive to the inputs and outputs selected for the model and it appears that the choice of input measures for insurance studies is more consistent than is the choice of output measures. Conventionally, it is assumed that insurance firms use labor, business services and material, financial equity and debt capital as inputs. Use of equity capital as an input has been justified by Cummins and Weiss (2001) and Cummins and Danzon (1997). In analyzing the efficiency of the insurance industry Greene and Segal (2004), Cummins et al. (1996), Chakraborty et al. (2012) used equity capital as an input. Eling and Luhnen (2010) found that 61 out of 95 studies used at least labor and capital as inputs, and that the most common form of broader expenditure category was total expenditure. Kao and Hwang (2007) used operating expenditure as an input. The current study uses operating expenditure, equity capital, and total investment as inputs for both life and non-life insurance firms. As noted by Eling and Luhnen (2010), there are generally three principle approaches used for measuring insurance industry outputs – the intermediation approach (Liverty and Grace 2008), the user-cost method (Cummins and Weiss 1993), and the value-added approach (Grace and Timme 1992; Berger at al. 2000).

The current study uses value-added approach in which the insurer is assumed to have provided three services: risk-pooling and risk-bearing services (collecting premiums from policy holders and redistributing them to customers who incurred losses); financial services (financial planning for life and design for coverage for non-life); and, intermediation services (investment of the premium on the capital market). Following Kao and Hwang (2007), and Chakraborty et al. (2013), we use net premium and income from investment as outputs for both life and non-life insurance firms in the DEA productivity measure. Most of the studies that applied regression analysis to explore the impact of firm specific and macroeconomic factors on efficiency and productivity changes used linear fixed and random effect models (Chen and Lee, 2014; Burca and Batrinca 2014; Dumpos and Gaganis 2012; Liverty et al. 2004). It is recognized in the literature that use of the linear model for panel data regression with a dependent variable which is limited to a value of between zero and one (efficiency scores are bounded by zero and one) may generate inconsistent results. Hence, some researchers suggest the use of tobit and/or truncated regression models which are more efficient and unbiased. The current study uses a panel dataset with a Tobit regression model to uncover the effects of firm-specific and macroeconomic variables on the components of productivity change indexes.

3. Methodology

3.1. Input Oriented DEA

The theoretical production functions are extremal and define the maximum output possible from a given set of inputs. In order to estimate the extremal production function for a multi-output technology the study uses a mathematical programming approach called data envelopment analysis (DEA), attributable to the pioneering works of Farrell (1957) and then Charnes et al. (1978) and Fare et al. (1985). The input-based frontier estimators in DEA enable construction of a nonparametric piecewise linear surface by enveloping the sample data with a convex hull consisting of a series of linear segments. The constructed reference surface provides an upper bound for technical efficiency as business units operating on this bound would be fully efficient.

Consider the activities of J firm units each employing N inputs to produce M outputs. Let $\boldsymbol{N}$ denote the $(I\times N)$ matrix of N inputs used by firm units with typical element x_{jn} denoting the nth input utilized by the jth firm unit. Let $\boldsymbol{M}$ represent the $(I\times M)$ matrix of M outputs of J different firm units, where the typical element y_{jm} denotes the mth output of the jth firm. Outputs and inputs are hypothesized to obey the usual nonnegativity restrictions. The piecewise linear input set, constructed under standard assumptions of constant returns to scale (C) and free/strong disposability of inputs (F), denotes all input vectors capable of producing at least output vector y:

$$L(y\,|\,C,F) = \{x : y \le z\mathrm{M}, z\mathrm{N} \le x, z \in \Re^{J}_{+}\}, y \in \Re^{M}_{+} \qquad (1)$$

where z denotes an $(1\times \mathrm{I})$ intensity vector that forms convex combinations (with variable returns) of observed input and output vectors. The technical efficiency of an observed firm is measured as a distance function measured from the candidate input vector towards the constructed piecewise linear, convex isoquant. The distance function measure seeks out a parameter of technical efficiency ξ such that, when multiplied to an inefficient firm's input bundle renders that firm efficient. The input-based distance function measure bounded by 0 and 1 can be written as:

$$D_i(y^j, x^j \mid C,F) = \mathrm{Min}\{\xi : \xi x^j \in L(y^j \mid C,F)\} \tag{2}$$

This input-oriented measure considers the equi-proportionate shrinkage in inputs required to project a firm back onto the frontier, while still maintaining the production of its given level of outputs. Solution of the following linear programming model consolidates equations (1) and (2) and obtains firm-specific technical efficiency measures relative to the bounding technology:

$$B_i(y^j, x^j \mid C,S) = \underset{\xi z}{Min}\,\xi \tag{3}$$

$$\text{S.t.} \quad y^j \leq z\mathrm{M}$$
$$z\mathrm{N} \leq \xi x^j$$
$$z \in \Re_+^J$$

If the input vector is on the boundary or frontier of technology, then the value of the distance function is one, implying the production is technically efficient. Otherwise, if it is less than one, then the production is technically inefficient. For the purpose of comparing efficiency measures based on variable or non-increasing returns to scale the constant returns to scale assumption is relaxed assuming, sum $z_j \leq 1$, called pure technical efficiency. Scale efficiency is measured as a ratio of technical efficiency under the assumption of CRS and VRS if equal to one implies the firm is scale efficient and if less than one the firm is scale inefficient. This occurs when the firm is producing increasing level of outputs in the phase of decreasing returns to scale (DRS) or producing lower level of outputs in the phase of increasing returns to scale (IRS).

3.2. Dynamic Productivity, Efficiency, and Technological Innovation

The above measures yield static descriptions of productivity. Dynamic productivity and efficiency estimates are derived using multi-period analysis. This study uses Malmquist productivity indexes, which use information on the input and output quantities to estimate productivity and productivity growth over time. The Malmquist productivity index (Fare et al. 1989) measures productivity differences across time periods, and generates a decomposition of the sources of dynamic productivity changes. Malmiquist index has been widely used for dynamic productivity analysis in the financial, insurance, and service sectors where input and output measures are not readily available (Aparicio et al. 2017; Chakraborty et al. 2013). Pastor et al. (2005) argue that the existing Malmquist productivity index developed and modified over the years (Caves et al. 1982; Diewert 1987; and Faire et al. 1996) is not circular, meaning its adjacent period technologies when used to decompose the index infeasibility in the linear programs can occur. Pastor et al. (2005) proposed a new global Malmquist index with technology formed from data of all producers in all periods. The index is circular in the sense it generates a single measure of productivity change and allows technical regress and it is immune to linear program infeasibility. The conventional Malmquist indexes are based on distance functions which rely on the primal description of technology. At each time period, t = 1, 2 ... T, technology is modeled as:

$$L^t(y_t \mid C,F) = \{x_t : y_t \le z\mathrm{M}_t, z\mathrm{N}_t \le x^t, z \in \Re_+^I\}, y^t \in \Re_+^{\mathrm{M}}. \tag{4}$$

The Malmquist input-based productivity index measures changes in performance during two time periods. Following Fare et al. (1994, 1996) the index can be decomposed into a measure of efficiency change and technical change.

$$\begin{aligned} M_i^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t \mid C,F) &= \left[\frac{S_i^t(y^t, x^t \mid C,F)}{S_i^t(y^{t+1}, x^t \mid C,F)} * \frac{S_i^{t+1}(y^t, x^t \mid C,F)}{S_i^{t+1}(y^{t+1}, x^{t+1} \mid C,F)} \right]^{1/2} \\ &= \frac{S_i^t(y^t, x^t \mid C,F)}{S_i^{t+1}(y^{t+1}, x^{t+1} \mid C,F)} \left[\frac{S_i^{t+1}(y^{t+1}, x^{t+1} \mid C,F)}{S_i^t(y^{t+1}, x^{t+1} \mid C,F)} * \frac{S_i^{t+1}(y^t, x^t \mid C,F)}{S_i^t(y^t, x^t \mid C,F)} \right]^{1/2} \end{aligned} \tag{5}$$

The term outside the square bracket, e.g., numerator and denominator of the ratio are the same as equation (1) with observations drawn from t and (t+1) period in order to specify year-specific input correspondences. The ratio captures the changes in efficiency between the two periods as measured by the ratio of two efficiencies. Both numerator and denominator of the ratio must be greater than or equal to one and the values closer to 1 represent higher efficiency. Hence, if technical efficiency is higher in period t compared to period (t+1), the value of the ratio will be greater than one and if the efficiency declines between two periods the value of the ratio will be less than 1. The two ratios within the square brackets can be thought of as a measure of technical change measured as the shift in the frontier at *(t+1)* and *t* periods where two measures of the shift are averaged geometrically. The whole term within the square bracket represents technical change, i.e. shift of the frontier between period t and (t+1) happens if both ratios comprising the geometric mean is greater than one called technical progress and a value less than 1 implies technical regress. Using this firm-specific productivity index it is possible to attribute the productivity growth to change in efficiency across time and shifts in the frontier due to technical innovations. Further, estimations of productivity under various returns to scale and disposability assumptions help find the sources and components of dynamic productivity changes such as pure technical efficiency changes, scale efficiency changes, and technical innovations. For further information on the use of DEA and Malmquist index in insurance firms please see Cummins et al. (1999), Cummins and Weiss (2001), and Chakraborty et al. (2012, 2013).

3.3. The Regression Model

Following Rezitis (2006) and Chakraborty et al. (2013), this study uses a limited dependent variable Tobit regression model to assess the relative contribution of variables associated with differences in total factor productivity and its components among firms. Firm characteristics and macroeconomic environment exogenous to the operating process are assumed to be the sources of differences in productivity levels, and are captured in the regression analysis. The three dependent variables in our regression model are the efficiency change index (EFFCH), the technological change index (TECHCH), and the total factor productivity change index (TFPCH). Since the lower limit for each of these indexes is zero by construction, parameter estimates obtained via least squares panel data models would be biased and inconsistent (McCarty and Yaisawrang 1993). The upper limit for these indexes can be above one. Hence, we use censored regression in the form of a basic Tobit model for panel data with the lower tail censored at zero. The Tobit model for panel data is written as:

$$y_{it}^{*} = z_{it}'\beta + \varepsilon_{it} \quad \varepsilon_{it} \sim \text{IN}\,(0, \sigma^2) \tag{6}$$

where $\;if\;\; y_{it}^{*} \leq 0\;$ the index for the *i*th firm in year t, $y_{it} = 0$,

The observed scores for each of these three indexes (EFFICH, TECHCH, and TFPCH) are censored values of y_{it}^{*}, censoring at zero and continuous above zero, which can be viewed as a threshold beyond which the environmental variable z_{it} must affect y_{it} to be seen.

4. The Dataset

The data for this study are collected from the Annual Report of the Insurance Regulatory and Development Authority (IRDA), government of India for various years. Currently there are 28 non-life insurance companies of which six are public sector companies and two are specialized insurers, namely, Agriculture Insurance Company Ltd., and Export Credit Guarantee Corporation of India for credit insurance. There are 24 life insurance companies operating in India and only one is a public-sector company. Not all companies were in operation from 2007-08, the beginning year of the study period. Due to non-availability of a consistent balanced panel of data for the entire study period (2008-2016), our panel data consist of 18 leading non-life firms (4 public firms and 14 private firms) and 14 life insurance firms (1 public and 13 private) observed over a period of 8 years. Firms were selected based on the volume of gross premium written and their respective market shares for life and non-life insurance market. The core business activities of an insurer are underwriting and investment, both of which affect the insurer's overall financial performance and efficiency. Hence, variables related to core business activities are included in the study.

The data availability for this study is restricted to the information submitted by the insurers in compliance with the regulatory authority in India. For the DEA and Malmquist productivity measure, the same inputs and outputs are used for life and non-life firms. The two outputs used are net premium written and income from investment; and the four inputs used are equity capital, total investment, total asset, and operating expenses. For consistency with the literature all inputs and output variables reported are in millions of US$, and are adjusted for inflation. Data on macroeconomic variables are collected from the Ministry of Labor, Government of India and National Statistical Services website. Descriptive statistics of the inputs and outputs used in this study are reported in Table 3 and Table 4.

The lower part of each table reports variables related to firm-specific and macroeconomic variables used in regression analysis. The firm characteristics such as distribution ratio, claims ratio, solvency ratio, and shareholder's equity to asset ratio are assumed to have a positive effect on the efficiency and productivity level of the firms. In addition, firm characteristics such as firm size (natural log of total assets) and market share (share in total premium written) are also included as independent variables in the Tobit model. Macroeconomic variables included are annual growth rate of GDP, deposit interest rate, trade freedom index, and business freedom index. Definitions of the variables used in this study are reported in Table 2.

5. Analysis of Results

5.1. Analysis of Productivity Indexes

Input-oriented annual mean pure technical efficiency and scale efficiency scores obtained from the DEA model are reported in Table 5. Firm level scores are not reported in this study since it is not a focus in this paper. For life insurers, pure technical efficiency increased marginally from 86.20 to 88.00 percent during the study period. Scale efficiency also increased marginally but on average firms are not scale efficient for the study period, with scores of less than 1.00. For life insurers, pure technical inefficiency is 12.90 percent (i.e., 1.00 – 87.10) which constitutes a larger source of inefficiency than scale inefficiency because scale inefficiency is only 5.00 percent (1.00 – 95.00). In other words, the main cause of inefficiency is failure of the firms to optimize the use of inputs for producing maximum outputs. For non-life insurers, pure technical efficiency decreased marginally and scale efficiency remained the same over the study period with some fluctuations over the years.

Firm-level Malmquist productivity indexes (mean) for the entire study period are reported in Table 6. These indexes are efficiency change (EFFCH), technological change (TECHCH), and total factor productivity change (TFPCH) and are reported in column 2, 3, and 4, respectively. The upper half reports the indexes for life and the lower half reports the indexes for non-life insurance firms. The value for any of these indexes if greater than one indicates improvement and less than one denotes deterioration in performance. For life insurance firms the results indicate that the overall total factor productivity for these firms (TFPCH) decreased by 11.8 percent [(1.00 – 0.88200*100] per year over the study period. This decrease in TFPCH can be decomposed into an efficiency change of +0.9 percent [(1.009 – 1.000)*100] and technological change (TECHCH) (technological regress) of -12.6 percent [(0.874 – 1.00)*100], where a decrease in TECHCH is called technological regress. An intuitive explanation for technological regress is that the life insurance firms in India need more inputs in 2016 compared to 2010 in order to produce a given level of output vector and become more productive and efficient. For example, TATA AIG is the only firm in the sample that achieved total factor productivity growth of 7.1 percent which is primarily due to improvement in efficiency by +8.9 percent while it has a technological regress by -1.7 percent during the study period. Using data from banking sector in Indonesia, Defung et al. (2017) found efficiency change is the main source for productivity improvement. For non-life firms (lower half of Table 5) total factor productivity change (TFPCH) decreased by 0.4 percent because a slight drop in technological change (TECHCH) (-0.8 percent) is matched by a small improvement in efficiency change (EFFCH) (+0.4 percent). Similar results were found by Chakraborty et al. (2012, 2013) for life and non-life firms using a different set of panel data.

5.2. Analysis of Regression Results

Each index obtained from Malmquist productivity analysis (EFFCH, TECHCH, and TFPCH) represents a change from the previous period. A magnitude greater than one represents improvement and less than one represents deterioration. Since our panel data is for 8 years (2007-08 to 2015-16) these change indexes are only obtained for the most recent 7 years. This reduces the number of years in our panel for the regression analysis to 7 years. Further, each index used as a dependent variable represents change from the previous year to maintain consistency all independent variables in the regression analysis are lagged by one year to capture their concurrent effect on the dependent variable. This study uses Tobit regression because the lower bound for the dependent variable is limited by zero while the upper bound is continuous. Theoretically, the upper limit for any of these indexes can be greater than one (for performance improvement).

Table 7 reports regression results for life insurance firms and Table 8 reports results for the non-life insurance firms. Model-1 represents results from regression using EFFCH as the dependent variable, Model-2 and Model-3 represent results using TECHCH and TFPCH as the dependent variable, respectively. Both fixed and random effect models are tested but the fixed effect model results fit the data better. Hence only fixed effect model results are reported. It is observed from Table 7, that the distribution ratio and claims ratio are mostly significant and negative for all three models. This suggests a higher commission paid (distribution ratio) and a higher net benefit paid (claim ratio) would reduce EEFFCH, TECHCH, and TFCPH. A positive and significant input cost ratio for Mod-1 and Mod-3 implies that an increase in input cost which improves the operational and organizational efficiency for the firm would lead to an increase in EFFCH and TFPCH. A positive and significant coefficient on firm size (log of fixed assets) in Model-1 and 3 implies larger firms have positive effect on the efficiency change index (EFFCH). Most of the studies in the literature have found firm size to have a positive effect on efficiency and profitability (Lee 2014; Elango et al. 2008; and Lee and Lee 2011). As expected, the sign on macroeconomic variables such as change in GDP and deposit interest rate are positive and significant for Model-2 and Model-3, which is consistent with the literature. One of the explanations for the positive effect of deposit interest rate is that life insurers depend heavily on their assets and liabilities, hence higher interest rates offer higher portfolio earnings leading to a positive effect on technological change and productivity change (life insurers offer savings products and guaranteed returns). The variance parameter sigma is highly significant for all three models which justifies fixed effect models as appropriate.

For non-life firms (Table 8) the coefficients on firm size are in general insignificant but have negative signs. One reason for the significant negative sign in Model-1 could be the drawback of the recent growth process of several non-life companies through merger and acquisition, as it is recognized that organizational strategy in firms in India may take several years to form. The other reason could be that intense competition among the biggest firms in the market is lowering the price for market share. The distribution ratio and claims ratio are generally significant and have expected the signs. The shareholder's equity-asset ratio has mixed signs and significance. This suggests that insurers' capital strength affects its technological change and total factor productivity change index negatively. Hence, for non-life firms, improving equity capital compared to total asset would lead to a reverse of this trend. The input cost ratio, though significant for Model-1 and Model-2, has mixed signs. Contrary to our expectation the deposit interest rate and growth in GDP have no effect on any of the models. However, the negative relationship between interest rate and technological and total factor productivity change is investigated by Albrecht (2003) using German data. His study found a higher interest rate would reduce the appraisal value of a non-life insurance firm if the company has predominantly long-term investments and a combined ratio greater than 100 percent. If the ratio is greater than 100 percent then a rising interest rate increases the competitive pressure, thus causing a negative effect on the present value. How that leads to a negative effect on technological change and total factor productivity change is unknown to the authors but could be a possible explanation. Further, a recent study by Venkateswarlu and Rao

(2016) found the overall combined ratio for non-life firms in India for the last decade remained as high as 114 percent due to heavy underwriting losses. For this study, it is safe to conclude that a higher interest rate lowers the value of the firm, leading to reduced productivity and technological change. The trade freedom index, which captures the regulatory conditions in the financial industry, is generally negative and significant for all three models. This suggests that the overall efficiency of government deregulations on trade and business has a negative effect on technology and total factor productivity change index. The highly significant sigma for all three models suggest that fixed effect models fit the data well.

6. Summary and Conclusions

This paper estimates dynamic productivity indexes and investigates the effects of firm-specific and macroeconomic factors on total factor productivity and its components for life and non-life insurers. Using DEA, the study estimated firm-level pure technical and scale efficiency using eight years of panel data. We found life insurers on average are 87.10 percent and non-life insurers are 90.80 percent efficient (Table 5). Dynamic productivity analysis using Malmquist productivity indexes found total factor productivity for life insurers on average decreased by 11.8 percent annually during the study period. The major cause for productivity decrease is technological regress. A possible solution for life insurance firms could be to increase underwriting performance. In India life insurance is the most preferred form of financial saving instrument among 23 percent of the households. Building cost effective distribution strategies, increasing policies' persistence with purchasers, and controlling expenses may lead to technical progress. Although non-life insurance firms in this study have a decrease in the technological change index of 0.8 percent, this is matched by a small increase (0.8 percent) in efficiency change index yielding an overall total factor productivity decrease by 0.4 percent annually.

Regression analysis found contrasting results for life and non-life firms mainly due to the differences in the nature of business being undertaken by the firms. However, the regression analysis revealed several interesting results. For life insurance firms, we found that a higher claims ratio and a higher distribution ratio reduce the efficiency, technology, and total factor productivity indexes. However, a higher input cost ratio increases efficiency and productivity. This suggests that increased expenses for firm operation and organization (part of the input cost ratio) would affect efficiency and productivity positively whereas, increased expenses on commission paid (distribution ratio) and net benefit paid (claims ratio) would affect efficiency and productivity negatively. A likely explanation for such a relationship is that increased input costs are associated with improved firm efficiency in doing business because higher management expense are a proxy for managerial efficiency. Several studies in the literature suggest that life insurers in India should focus on cost effective distribution strategies, use of digital technology to enhance products and services delivered to the policy holders, and better connected partners and providers (InGuard 2015). It is also observed that cost control initiatives for Indian life insurers have led to a higher cost efficiency but have also reduced the growth of new businesses. According to SwissRe (2016) worldwide it is expected that the life insurers will continue to focus on improving capital management, lowering expenses, and enhancing investment yields. Consistent with expectations for the life insurance business, the study found that the distribution ratio and the claims ratio for non-life businesses are generally negative and significant. Interestingly, the input cost ratio has a reverse relationship for life and non-life business. For life, the coefficient is positive and for non-life it is generally negative.

The general effect of macroeconomic variables for life insurance firms is as expected except that the trade freedom index, although generally positive, is mostly insignificant for all three models. For non-life firms the interest rate and GDP growth have no effect on any of the three indexes. Several other studies using data from the Indian insurance market also found a high combined ratio for non-life firms during the same study period as the current study (Best, 2014). It clearly has become necessary for insurance firms to improve operating performance, as profitability is affected due to intense competition after a decade of deregulation in the insurance industry in India. The main challenges for the industry are adequate pricing, distribution, and cost efficiency. For India, with insurance penetration for life 2.72 percent and non-life 0.72 percent of GDP there is a huge potential for the market to grow. We suggest Indian insurance firms should focus on the redesigning channel strategy and financial awareness of the customers.

Endnote

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Table 1: Insurance Density and Penetration for Life and Non-life Insurance for India vis-à-vis Selected Asian Nations – 2015

	Growth in	Insurance Density (UD$)		Insurance Penetration (%)	
Country	RGDP	Life	Non-life	Life	Non-life
Brazil	-3.8	178.3	153.7	2.09	1.80
Russia	-3.7	14.8	102.3	0.17	1.19
PR China	6.9	153.1	127.6	1.95	1.63
India	7.3	43.2	11.5	2.72	0.72
S. Africa	1.3	687.9	154.6	12.00	2.70
Singapore	2.0	2931.5	893.7	5.55	1.69
Malaysia	5.0	315.6	156.7	3.37	1.68
Thailand	2.8	215.1	103.9	3.70	1.79
Sri Lanka	6.2	18.5	24.5	0.49	0.66
Philippines	5.8	39.8	15.3	1.37	0.53
Indonesia	4.8	42.7	15.2	1.28	0.45
Pakistan	4.2	7.7	3.9	0.54	0.27
Asia	4.5	209.8	102.0	3.59	1.74
World	2.5	345.7	275.6	3.47	2.77

Source: Swiss Re Sigma No. 3/2016
Insurance density is measured as a ratio of premiums to total population and expressed in US$. The insurance penetration is measured as a ratio of premiums to GDP. A few developed and developing countries in South Asia are included in the table.

Table 2: Description of Variables used (Life = 14, Non-life = 18) Years - 2009-16

Firm Characteristics	VARS	Description
Firm size	LFASS	Ln(fixed asset)
Firm stability	LNCP	Ln(net claims paid) OR Ln(net benefit paid)
Investment yield	INY	Net investment income/liquid.asset + tot.investment
Distribution ratio	DNR	Commission paid/total cost incurred
Claims ratio	CLR	Net benefit paid (life) OR net claim incurred (non-life)/gross premium written
Shareholders E-A-Ratio	SEA	Equity capital/total asset
Input cost ratio	ICR	Total expenses (opr+org exp)/gross premium written
Solvency ratio	SOL	Total capital to total asset
Market share	SHR	Percent of gross premium written out of total premium
Macro Variables		
Financial openness Index	BFI	Heritage financial freedom index
Trade Freedom index	TFI	Heritage trade freedom index
Annual growth of GDP	CGDP	Change in growth of GDP
Deposit interest rate	DRI	Savings bank long term deposit interest rate

Table 3: Descriptive statistics of the Life Insurance Variables (Inflation adjusted $ Million)

Variable	Mean	SD	Min	Max
DEA - Outputs				
Net premium written	3493.11	9200.21	24.89	4277.87
Income from Investment	890.50	6102.41	4.56	6238.06
DEA - Inputs				
Operating Expenditure	365.76	700.83	4.74	3742.21
Equity capital	361.47	233.01	46.31	1006.57
Total investment	14146.5	4883.94	54.89	250299
Total asset	1550.55	53161.13	59.70	271261
Regression - Dependent Variables				
Efficiency change (EFFCH)	1.012	0.143	0.684	1.700
Technological change (TECHCH)	0.914	0.236	0.050	1.741
Total factor productivity change (TFPCH)	0.931	0.275	0.490	1.605
Regression - Independent Variables				
Fixed asset (FASS)	56.742	137.10	0.750	655.900
Net benefit paid (NBP)	1938.3	5373.8	1.280	24886.8
Distribution ratio (DNR)	26.546	10.811	9.960	73.680
Claims ratio (CLR)	53.650	39.424	3.150	174.360
S.H. equity to asset ratio (SEA)	49.859	48.605	0.040	228.450
Input cost ratio (ICR)	27.608	12.711	11.740	115.230
Market share (SHR)	6.980	18.141	0.050	75.390
Solvency ratio (SOL)	3.211	1.477	1.540	7.610
Growth in GDP (CGDP)	7.493	1.404	5.620	10.260
Deposit interest rate (DIR)	8.686	0.542	7.500	9.250
Trade freedom index (TFI)	61.071	6.507	51.000	67.900
Business freedom index (BFI)	41.286	7.315	35.500	54.400

Table 4: Descriptive statistics of the Non-Life Insurance Variables (Inflation adjusted $ Million)

Variable	Mean	SD	Min	Max
DEA - Outputs				
Net premium written	414.79	444.24	0.09	2078.88
Income from Investment	32.35	46.68	0.61	199.22
DEA - Inputs				
Operating Expenditure	109.78	114.33	1.46	465.68
Equity capital	50.13	36.95	14.91	189.02
Total investment	1038.63	1457.91	6.12	6705.63
Total asset	1423.80	1951.42	22.92	6124.96
Regression - Dependent Variables				
Efficiency change (EFFCH)	1.010	0.165	0.628	1.754
Technological change (TECHCH)	1.012	0.231	0.423	1.819
Total factor productivity change (TFPCH)	1.003	0..211	0.502	1.809
Regression - Independent Variables				
Fixed asset (FASS)	15.742	15.364	0.910	79.980
Net claims paid (NCP)	347.562	374.660	0.470	1668.62
Distribution ratio (DNR)	8.785	40.630	-128.82	205.810
Claims ratio (CLR)	56.800	12.771	8.000	85.540
S.H. equity to asset ratio (SEA)	14.488	14.105	0.3360	55.300
Input cost ratio (ICR)	25.367	18.385	-7.950	157.830
Market share (SHR)	5.2944	4.952	0.090	19.240
Solvency ratio (SOL)	2.522	2.554	1.020	16.420

Table 5: Annual Means for Pure Technical and Scale Efficiency Scores 2008-09 to 2015-16

	2009	2010	2011	2012	2013	2014	2015	2016	Average
Life									
P-Effi	0.862	0.839	0.874	0.892	0.881	0.876	0.868	0.880	0.871
S-Effi	0.931	0.918	0.913	0.971	0.962	0.978	0.970	0.960	0.950
Non-life									
P-Effi	0.941	0.901	0.900	0.876	0.903	0.921	0.933	0.895	0.908
S-Effi	0.886	0.869	0.944	0.911	0.915	0.939	0.954	0.929	0.918

P-Effi = Pure technical efficiency; S-Effi = Scale efficiency (ratio of P-Effi under CRS and VRS)

Table 6: Firm Level Malmquist Productivity Index Summary, 2010-2016

Life	EFFCH	TECHCH	TFPCH
1. AVIVA	1.025	0.862	0.884
2. AJAJ ALLIANZ	1.000	0.901	0.901
3. BSLI	1.000	0.807	0.807
4. ING VYSYA	0.988	0.911	0.900
5. HDFC STD LIFE	1.034	0.932	0.964
6. ICICI PRU	1.009	0.908	0.917
7. KOTAK LIFE	0.955	0.855	0.817
8. MNYL	1.055	0.909	0.959
9. MET LIFE	1.013	0.900	0.912
10. RELIANCE LIFE	0.934	0.813	0.759
11. SAHARA	1.036	0.824	0.853
12. SBI LIFE	1.000	0.957	0.957
13. TATA AIG	1.089	0.983	1.071
14. LIC	1.000	0.713	0.713
Mean	1.009	0.874	0.882
Non-Life			
1. NEW INDIA	1.000	1.010	1.010
2. NATIONAL	1.000	1.106	1.106
3. ORIENTAL	0.949	1.032	1.008
4. UNITED	0.990	0.994	0.984
5. ECGC	0.968	0.901	0.872
6. AIC	1.000	1.006	1.006
7. BAJAJ ALLIANZ	1.000	1.101	1.101
8. ICICI LOMBARD	0.970	1.069	1.037
9. IFFCO TOKIO	1.000	1.098	1.098
10. RELIANCE	0.952	0.982	0.935
11. ROYAL SUNDARAM	0.981	0.993	0.974
12. TATA-AIG	1.026	0.993	1.020
13. CHOLAMANDALAM	1.007	1.039	1.046
13. HDFC CHUBB	1.003	0.972	0.975
15. STAR HEALTH	1.000	0.987	0.987
16. APOLLO DKV	1.092	0.873	0.953
17. FUTURE GENERALI	1.175	0.846	0.995
18. UNIV SOMPO	0.971	0.885	0.860
Mean	1.004	0.992	0.996

EFFCH = technical efficiency change; TECHCH = technological change
TFPCH = total factor productivity change;
TFPCH = EFFCH + TECHCH

Table 7: Fixed Effect Tobit Regression – Effects of Firm Specific and Macroeconomic Factors on Dynamic Productivity Indices – Life Insurance Firms (2010-16)

	Model 1		Model 2		Model 3	
	Dep var = EFFCH		Dep var = TECHCH		Dep var = TFPCH	
Variables	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat
Ln (fixed asset)	0.0430**	2.54	0.0053	0.23	0.0467*	1.79
Distribution ratio	-0.0040*	-1.79	-0.0036	-1.19	-0.0088**	-2.54
Claims ratio	-0.0014**	-2.09	-0.0016*	-1.80	-0.0034***	-3.35
S. Hold equity-asset R	-0.0010*	-1.84	0.0016**	2.11	0.0005	0.60
Input cost ratio	0.0044***	2.81	0.0029	1.38	0.0064***	2.66
Solvency ratio	0.0259*	1.76	-0.0079	-0.42	0.0147	0.68
Percent change in GDP	-0.0018	-0.06	0.1656***	3.390	0.2005***	4.12
Deposit interest rate	-0.0062	-0.08	0.7243***	6.71	0.8207***	6.63
Trade freedom index	-0.0003	-0.10	0.0036	0.95	0.0049	1.12
Sigma	0.1223***	14.00	0.1348***	14.00	0.1887***	14.00
LLF	65.6266		36.7501		23.5776	
Observations	98	---	98	---	98	---

***, **, * denote significance at 1%, 5%, and 10% level
EFFCH = technical efficiency change; TECHCH = technological change
TECHCH = technological change; TFPCH = total factor productivity change

Table 8: Fixed Effect Tobit Regression – Effects of Firm Specific and Macroeconomic Factors on Dynamic Productivity Indices – Nonlife Insurance Firms (2010-16)

	Model 1		Model 2		Model 3	
	Dep var = EFFCH		Dep var = TECHCH		Dep var = TFPCH	
Variables	Coefficient	z-stat	Coefficient	z-stat	Coefficient	z-stat
Ln (fixed asset)	-0.3555	-1.55	-0.0351	-1.06	-0.0691**	-1.98
Distribution ratio	0.0003	1.09	-0.0014***	-2.82	-0.0011**	-2.27
Claims ratio	-0.0038***	-2.81	-0.0015	-0.75	-0.0047**	-2.28
S. Hold equity-asset R	0.0072***	2.88	-0.0099***	-2.76	-0.0037	-0.99
Input cost ratio	0.0052***	5.59	-0.0026*	-1.96	-0.0073	-0.51
Solvency ratio	0.0046	0.45	-0.0002	-0.02	-0.0004	-0.03
Percent change in GDP	-0.0374	-1.38	0.0005	0.01	-0.0447	-1.08
Deposit interest rate	0.0087	0.13	-0.0072	-0.07	-0.0395	-0.37
Trade freedom index	0.0046**	2.11	-0.0168***	-5.36	-0.0113***	-3.41
Sigma	0.1138**	15.87	0.1651***	15.87	0.1730***	15.87
LLF	93.74		47.30		41.44	
Observations	126	---	126	---	126	---

***, **, * denote significance at 1%, 5%, and 10% level
EFFCH = technical efficiency change; TECHCH = technological change
TECHCH = technological change; TFPCH = total factor productivity change