Multi-Directional Efficiency Analysis of Ghanaian Life and Non-Life Insurers in the Presence of Undesirable Output.

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Abstract

The study evaluates the input/output efficiencies of insurers in Ghana, highlighting the misleading results in insurance efficiency assessment when undesirable outputs are excluded from efficiency estimations. Using a panel data set of 30 life and non-life insurers from 2008 to 2019, the multi-directional efficiency analysis is used to assess aggregated and disaggregated efficiency levels. Robust econometric regression models (pooled ordinary least squares and two-step system Generalized Method of Moment (GMM)) are also used to investigate the external factors that affect comprehensive efficiencies.
Investment income was identified as the worst-performing insurer output variable, reducing the overall efficiency of insurers. Claims, representing an undesirable variable, was identified as the best-performing variable in raising overall efficiency, followed by labour. Life insurers are observed to be performing significantly better than their non-life counterparts on their aggregated and disaggregated efficiency. Finally, the previous year's overall performance of insurers and the level of competition are identified as the determinants of insurance efficiency.

Key words: claims, insurance, multi-directional efficiency analysis, second-stage analysis, undesirable output.

1. Introduction

The insurance sector is a key driver of economic growth because it fosters investment, ensures efficient resource allocation, encourages cost reduction through liquidity creation, provides financial assistance to people and businesses during losses, and generates employment (Lee et al., 2013). Still, the Ghanaian insurance sector has been fraught with several challenges, including premium undercutting, motor insurance fraud, and inefficiency (NIC 2017). Consequently, significant regulatory reforms have occurred, namely, the segregation of life and non-life insurers, the abolition of premium credit in the insurance market, an increase in minimum capital requirements for all insurers, efficiency improvements, and risk management (Kusi et al., 2020; NIC, 2018). Despite these efforts, insurance penetration is minimal in the country (NIC 2019, 2011), highlighting the prevailing challenges in reaching broader markets in Ghana. Given the role of the insurance sector, the competitive landscape, reforms, the role of claims, and the implications for business failure, researchers, managers, and policy makers have taken an interest in assessing the efficiency of insurers (Eling & Jia, 2018; Kaffash et al., 2020). However, despite the number of Ghanaian insurance efficiency studies (Owusu-Ansah et al., 2010; Ansah-Adu et al., 2012; Kusi et al., 2020) that have examined some of these reforms, there is a dearth of study on the input/output efficiency of Ghanaian life and non-life insurers.

Insurance in Ghana commenced in 1924, dominated by foreign insurers primarily providing coverage to British nationals (Ansah-Adu et al., 2012; Alhassan et al., 2015). Local coverage started in 1955 with the establishment of the Gold Coast Insurance Company to provide life policies to its citizens and other African nationals. In 1958, another local insurance company was established to mainly underwrite fire and motor insurance businesses in the country, leading to major consolidation efforts that necessitated the creation of the State Insurance Corporation (SIC). Subsequently, several legislative efforts were taken that laid the foundation for a regulated, growth-oriented sector. The Insurance Act 2003 allowed insurers to operate as composite insurers until it was replaced with the Insurance Act 2006 (Act 724), which required the separation of life and non-life insurance businesses. Currently, the industry operates under the Insurance Act 2021, which seeks to protect the introduction of new compulsory insurances. The industry is currently fraught with several efficiency estimation challenges, particularly with the role of claims and the efficiency performance of life and nonlife insurers (Alhassan & Biekpe, 2016; Alhassan et al., 2015).

Data Envelopment Analysis (DEA) has been widely used for assessing the efficiency of insurers (Kaffash et al., 2020) but has been criticized as providing partial insights into the aggregated efficiency of firms instead of a completely disaggregated efficiency that captures the contribution of individual-specific inputs and outputs (Asmild & Matthews, 2012; Kapelko & Lansink, 2017; Tziogkidis et al., 2020). Underpinned by the decision theory of Hansson (2005), claims of a particular insurer can contribute significantly more to the overall efficiency than other inputs, labour, or other outputs, and net premiums. Thus, it is necessary to select benchmarks such that the non-radial adjustments to the inputs and outputs correspond to the potential improvements identified by considering the improvement potential in the variables separately (Asmild & Matthews 2012). It is worth noting that previous insurance efficiency studies based on Charnes et al. (1978) have modelled claims as an input (Gaganis et al., 2013; Wu et al., 2007). However, similar to the production processes in the energy and banking sectors, insurance production is undertaken with the motive of generating more benefits (creating positive value and destroying negative value) than costs (consuming positive value and generating negative value) but also produces bad output, an undesirable output. Even so, claims, an undesirable output of insurers, have not been incorporated as a negative by-product in the modelling behavior of insurance firms.

The selection of claims as an input or output has been argued in different insurance studies. There is no obvious trend in the literature specifying the ideal use of claims for appropriate insurance efficiency assessment (Gaganis et al., 2013). Studies like Gaganis et al. (2013), Rai (1996), Wu et al. (2007), Yang (2006), and Yao et al. (2007) captured claims as an input, with the analogy that claims form part of insurers' expenses and thus must be minimized, while overlooking the theoretical grounding of the multi-criteria theory (MCPT), which distinguishes between desirable outputs (benefits) and undesirable outputs (costs or losses). Whereas claims are the results of fulfilling insurance contracts, non-performing loans are the results of bank lending, and management is not interested in increasing them, even though they qualify as output variables (Diacon et al., 2002; Reyna & Fuentes, 2018). Although both remain integral to the service delivery process, they signify performance losses rather than profits. Thus, ignoring the undesirable nature of claims in efficiency assessment may distort conclusions.

To the best of our knowledge, this is the first study to examine the disaggregated view of insurance efficiency estimates via the contributions of individual inputs/outputs using the innovative MEA and also assess the possible impact of an undesirable output in insurance efficiency examination. We select benchmarks such that the non-radial adjustments to the inputs and outputs correspond to the possible improvements identified by considering the individual improvement potential in the variables. Given the non-parametric nature of MEA scores and their sensitivity to extreme data points, outliers, and sampling variations, the study further investigates the determinants of overall efficiencies using robust econometric regression models. In this regard, we contribute to the literature as we mathematically model claims as an undesirable output using the non-radial, non-oriented, multi-directional efficiency (MEA) of Bogetoft and Hougaard (1999) and Asmild et al. (2003). Again, we contribute by investigating the variable-specific efficiencies of some life and non-life insurers in Ghana. Finally, we contribute by assessing the impact of external factors on the overall efficiency using robust econometric regression models.

We find that the use of claims as a desirable output does not provide the appropriate claim performance level for insurers. Second, the sole use of the comprehensive efficiency of insurers does not provide accurate information on the utilization and generation of the input and output variables of insurers, respectively. Third, Ghanaian life insurers are more efficient than Ghanaian non-life insurers. Finally, the level of competition in the insurance industry has the highest impact on the performance of Ghanaian insurers, followed by the previous year's performance of insurers.

The rest of the study is organized on the following lines. The next section reviews related literature. Sections 3 and 4 describe the dataset of the Ghanaian insurance sector and the MEA model, respectively. The last two sections present the study findings and conclusion, respectively.

2. Relevant literature review

Insurance efficiency analysis has attracted significant interest in developing countries like Canada, India, and the Gulf Cooperation Council Countries (GCC) (Al-Amri et al., 2012, Siddiqui 2021). However, very few studies have been undertaken in sub-Saharan Africa (SSA). In one of such studies, Sharew and Fentie (2018) used DEA to empirically assess the efficiency of Ethiopian insurance companies. The study findings revealed less than 100% scale and overall efficiency score for Ethiopian insurers. Company size and branches were shown as significant determinants of the Ethiopian insurance efficiency. Similarly, Wasseja and Mwenda (2015) used DEA to assess the insurance efficiency of life assurance companies in Kenya. Their results highlighted a statistically significant decline in efficiency from 2004 to 2009 in Kenya. The regression analysis on the external factors revealed a significant impact of firm size and stock exchange listing on the technical efficiency of insurance firms in Kenya. Fotova et al. (2024) recently examined insurance efficiency in developing countries. Employing the input-oriented BCC DEA model, the study findings highlighted unstable, fluctuating efficiency levels within the North Macedonia insurance sector. Their findings emphasized the need for productivity and sustainability-enhancing reforms in developing countries. In the Ghanaian context, Ansah-Adu et al. (2011) used a cross-sectional dataset of 30 insurers to investigate the cost efficiency of Ghanaian insurers from 2006 to 2008. Their results showed that life insurers had higher average efficiency scores than non-life insurers. Danquah et al. (2018) also sampled 30 insurers to investigate the cost efficiency of Ghanaian insurers from 2005 to 2014. The study findings highlighted the low performance perception in the Ghanaian insurance sector. In terms of external factors, size, market share, capitalization, reinsurance, regulation, and business type were shown to explain cost efficiency.

The production of undesirable outputs from the agricultural, energy, and manufacturing sectors has received much attention from environmental policymakers (Khan et al. 2018; You and Yan 2011). Several studies have been carried out to effectively assess their performance while considering the production of these undesirable outputs (Bi et al., 2014; Zhu et al., 2019). Yang (2006) introduced a new two-stage DEA model that assessed systematic efficiency for the Canadian Life and Health (L & H) insurance industry. The study results demonstrated that the Canadian L & H insurance industry operated fairly during the period under study, 1996-1998. Another insurance efficiency study investigated whether the capital market considered insurance efficiency, sampling 52 countries from 2002 through 2008 (Gaganis et al., 2013). The study used the stochastic frontier analysis to estimate profit efficiency and controlled for country-specific characteristics. Claims were used as an input variable following Rai (1996) assertion of claims as an integral and important part of the annual expenses of insurers and the purpose of the study. The efficiency scores were further regressed with the stock returns and the results revealed a positive and statistically significant relationship between the current and past profit efficiency scores and market-adjusted stock returns.

Over the years, various techniques have been developed to measure efficiency performance in the presence of undesirable outputs (Chen et al., 2017; Dyckhoff & Allen, 2001; Sueyoshi & Goto, 2010; Maghbouli et al., 2014) due to the inability of the traditional DEA to compute efficiency scores in the presence of undesirable variables (Färe & Grosskopf, 2004; Seiford & Zhu, 2002). Asmild and Matthews (2012) is the first study that used MEA to assess the efficiency performance of Chinese banks while capturing one of its output variables as an undesirable output, non-performing loans. Following Thanassoulis et al. (2008), non-performing loans, an undesirable output, was used as an input in addition to three other inputs, namely labour, fixed assets, and bank deposits. The study findings were in contrast with popular findings, as JSBs were shown to be more efficient than the SOBs. Zhu et al. (2019) used an improved MEA approach to evaluate energy efficiency while considering the slack problem of production. Their findings revealed the country's provincial energy to be olive-shaped with significant spatial imbalance. In addition, their findings identified a large potential value for CO_2 emission in the Central region, with a relatively large energy-saving potential for the two other regions, Western and Eastern. In another study, Bi et al. (2014) aimed to gain deeper insight into the regional energy and environmental efficiency of the Chinese transportation sector. The authors adopted the modified MEA model to investigate the levels and patterns of efficiency. The results showed numerous efficient regions with a greater chance of reducing CO_2 emissions and energy consumption.

3. Methodological framework

3.1 Multi-directional Efficiency Analysis

Multi-directional efficiency analysis (MEA) is a DEA modification that separates the issue of benchmark selection from the issue of efficiency measurement (Bogetoft & Hougaard, 1999; Kapelko & Lansink, 2017; Labajova et al., 2016). The model was postulated by Bogetoft and Hougaard (1999), who provided an axiomatic foundation that supports the implicit benchmark selection over the potential improvement selection approach. Asmild et al. (2003) further operationalized the potential improvement approach with DEA and proposed the name multi-directional efficiency analysis (MEA).

The model consists of two stages: ideal reference point identification and improvement potential point selection for each input/output variable (Asmild et al., 2003; Asmild & Matthews, 2012). Unlike DEA, the selection of input reduction and output expansion benchmarks for MEA is based on the specified improvement potential related to each input and output separately (Asmild et al., 2003; Asmild et al., 2016). In an MEA input-oriented analysis, the largest reduction potentials for each input are identified and combined with the minimum possible input usage in each dimension to identify the ideal reference point (Asmild et al., 2003; Asmild & Pastor, 2010). The difference between the unit under analysis and the ideal reference point is used to find the directional vector of each unit (Asmild & Pastor, 2010).

Bogetoft and Hougaard (1999) and Asmild et al. (2003) have discussed some desirable properties of the MEA model over the traditional DEA. First, unlike DEA, which selects both weakly and strongly efficient benchmarks, MEA selects only strongly efficient benchmarks. Second, because of its non-radial improvement approach, MEA explicitly recognizes improvement potentials between input and output dimensions. Third, MEA can be extended to estimate efficiency under input orientation, output orientation, and non-orientation (input reduction and output augmentation simultaneously). Fourth, MEA can be extended to include discretionary and non-discretionary variables simultaneously. Finally, MEA can be run under both the constant return to scale and variable return to scale (VRS) technology; it is invariant to affine transformation under the VRS technology.

3.2 Multi-directional Efficiency Analysis Model

The study formalized an MEA model in line with Asmild and Matthews (2012) and Zhu et al. (2019) to investigate the input/output insurance efficiency of Ghanaian life and non-life insurers. (x_{i0}, y_{r0}, c_{k0}) is chosen as the production plan for $decision\ making\ unit_0\ DMU_0$. For each input, desirable output, and undesirable output variable, an ideal reference point is obtained. Then, the MEA efficiency of each variable for the production unit (x_{i0}, y_{r0}, c_{k0}) is derived as shown in **expression (1).**

$\beta_{r0}, \beta_{k0}, \beta_{i0}$ measures the proportion by which the desirable outputs are added while the undesirable outputs and inputs are contracted in the same proportion (Bogetoft & Hougaard 1999; Tziogkidis et al., 2020). Using the optimal solution, $(\lambda_j^*, \beta_{i0}^*, \beta_{r0}^*, \beta_{k0}^*)$, from equation (6), the benchmark selection for the target unit (x_{i0}, y_{r0}, c_{k0}) is determined as $(x_{i0}^*, y_{r0}^*, c_{k0}^*)$.

3.3 Robust Econometric model

The sensitivity of non-parametric efficiency models (DEA) to outliers and sampling variations makes it unsuitable to solely depend on efficiency scores to make statistical inferences (Daraio & Simar, 2007). Besides, environmental variations around firms cannot be overlooked, considering their direct impact on firm performance (Dyson et al. 2001). As a result, the assessment of the robustness of non-parametric efficiency scores, second-stage analysis, cannot be ignored during efficiency assessment.

With a baseline panel model (c.f. equation 2) an array of econometric techniques are employed to establish the strength of the results with the insurance-specific factors.

Expression (1)

$$max(\beta_{i0} + \beta_{r0} + \beta_{k0})$$

$$\text{subject to} \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0} - \beta_{i0}(x_{i0} - d_{i0}^*), i = 1, \dots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} - \beta_{r0}(\delta_{i0}^* - y_{r0}), r = 1, \dots, s_1 \\ \sum_{j=1}^{n} \lambda_j c_{kj} = c_{k0} - \beta_{k0}(c_{k0} - \phi_{i0}^*), k = 1, \dots, s_2 \\ \lambda_j \geq 0, j = 1, \dots, n \end{cases} \quad (1)$$

$$Eff_{i,t} = \beta_1 comp_{i,t} + \beta_2 lev_{i,t} + \beta_3 size_{i,t} + \beta_4 solv_{i,t} + \beta_5 roa_{i,t} + \beta_6 type_i + \beta_7 Underisk_{i,t} + \delta Eff_{i,t-1} + \sum_{t=2008}^{2019} Year_t + \sum_{i=1}^{30} Insurer_i + \varepsilon_{i,t} \quad \varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2) \quad (2)$$

where;

$\boldsymbol{Eff_{i,t}}$ = MEA efficiency score of insurer $\boldsymbol{i}$ at time $\boldsymbol{t}$;

$\boldsymbol{\beta_{i,i=1,\ldots,7}}$ and $\boldsymbol{\delta}$ are parameters to be estimated to assess the extent to which each explanatory variable influences the dependent variable;

$\boldsymbol{comp_{i,t}}$ = competition among insurers proxied as the Boone indicator for insurers $\boldsymbol{i}$;

$\boldsymbol{Eff_{i,t-1}}$ = the previous year's MEA efficiency score;

$\boldsymbol{lev_{i,t}}$ = leverage ratio of insurer $\boldsymbol{i}$ at time $\boldsymbol{t}$;

$\boldsymbol{type_{i}}$ = dummy variable with a value of 1 if the insurer deals with life business and 0 otherwise; $\boldsymbol{size_{i,t}}$ = size;

$\boldsymbol{solv_{i,t}}$ = solvency of insurer $\boldsymbol{i}$ at time $\boldsymbol{t}$ proxied with the z-score;

$\boldsymbol{roa_{i,t}}$ = profitability of insurer; $\boldsymbol{i}$ at time $\boldsymbol{t}$ proxied as the return on assets;

$\boldsymbol{Underisk_{i,t}}$ = underwriting risk of insurer $\boldsymbol{i}$ at time $\boldsymbol{t}$; $\boldsymbol{\sum_{t=2008}^{2019} Year_t}$, $\boldsymbol{\sum_{i=1}^{30} Insurer_i}$, $\boldsymbol{\varepsilon_{i,t}}$ are the time-dependent effect, the unobserved individual-specific effect, and the error term, respectively. These assume that the residuals are normally distributed with a zero mean and a constant standard deviation, $\boldsymbol{\varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2)}$. The subscripts: $\boldsymbol{i}$ and $\boldsymbol{t}$ denote the insurers being considered and the time period of the study, respectively.

Several econometric tests are undertaken to determine the appropriate and robust static regression model (pooled ordinary least squares (POLS), fixed/random effect model (FE/RE), random effect heteroskedasticity and autocorrelation-consistent (RE-HAC), panel-corrected standard errors regression (PCSE), and the Driscoll-Kraay standard error (SCC)) for the study, in addition to the two-step systems GMM (an instrumental variable regression) to cross-check the robustness of the MEA efficiency scores. The two-step system GMM is used to estimate the dynamic frontier with time-invariant technical efficiency (Bhattacharyya, 2012), like the MEA. Even though the static panel models control for unobserved heterogeneity and ensure unbiased estimates, they do not make room for endogenous regressors, which are common in real market systems. In addition to the above reasons, the two-step system GMM is suitable for small spans (T) and large units (Jin et al., 2021); thus, the two-step system GMM is chosen as the preferred model.

4. Data and variable selection

Following the separation of the composite insurers into life and non-life groups in December 2006, both life and non-life insurers were sampled to assess the group/individual comprehensive and variable-specific efficiency differences. Hence, 13 life and 17 non-life insurers that had been in operation from 2008 to 2019 were sampled for the study. The study data was retrieved from the statement of financial position and comprehensive income in the audited annual reports submitted to the National Insurance Commission (NIC).

4.1 Output

Outputs chosen for this study are based on the value-added approach since it reflects the basic services offered by insurers: risk-pooling and risk-bearing, intermediations, and real financial services related to insured losses. Investment income, net premium, and claims are chosen as outputs for the study despite the prevailing criticisms by Cummins and Weiss (2013) and Alhassan and Ohene-Asare (2016) on the use of net premium as an output, while a revenue, a product of price and output.

Following the return insurers receive from investment income and the opportunity insurers have to receive premiums in advance, in addition to their ability to make returns from premiums before the occurrence of a covered loss, investment income ($\boldsymbol{Y1}$) and net premiums ($\boldsymbol{Y2}$) are used as desirable outputs in this study (Cooper et al., 2011; Seiford & Zhu, 2002) whereas, claims ($\boldsymbol{C1}$) is used as an undesirable output (bad output).

4.2 Input

Three inputs are chosen to compute comprehensive and variable-specific efficiency scores: fixed assets ($\boldsymbol{X1}$), labour ($\boldsymbol{X2}$) and equity capital ($\boldsymbol{X3}$).

4.3 Variable Description

Table 1 reveals some pertinent observations in the Ghanaian insurance industry. First, the standard deviation of the insurers exceeds their mean values (both inputs and outputs). This is to say, insurers operating in Ghana vary in the size of inputs used and outputs produced. Second, there is a 0.01%, 1%, and 5% significant difference in the amount generated from net premium, claims, and investment income, respectively. Third, non-life insurers were observed to have insignificantly higher levels of inputs, labour costs, fixed assets, and equity capital than life insurers. However, the sampled life insurers generated significantly larger levels of desired and undesirable outputs, net premium, investment income, and claims than non-life insurers.

Table 1: Descriptive statistics of input/output (pooled data and business type, 2008 - 2019)
All monetary values are in GHS.

		Fixed capital $X1$	Labour $X2$	Equity capita $X3$	Net premium $Y1$	Investment income $Y1$	Claims $C1$
Pooled	Count	360	360	360	360	360	360
	Mean	4920182	14340536	28640604	31835053	9223024	13885505
	Std Dev	8443171	47262441	44835844	53498534	19289031	25518283
	Min	12664	6425	16874	361428	17285	36212
	Max	97518606	873230010	397215400	416881000	132015000	211855714
Time difference	F-statistics	46.45***	2.225	33.75***	57.7***	5.326*	9.745**
<u>Business type groupings</u>							
Life	Count	156	156	156	156	156	156
	Mean	4137251	11572050	27217164	43804573	9223024	20336154
	SD	6574524	14033169	40311535	75200414	19813382	35465612
	Max	42544569	68561000	220703000	416881000	94960139	211855714
	Min	12664	6425	211551	457873	37387	42728
Non-life	Count	204	204	204	204	204	204
	Mean	5518894	16457613	29729118	22681891	7008989	8952656
	SD	9603867	61559293	48078595	23437303	18624616	11609174
	Max	97518606	873230010	397215400	111847000	132015000	60889727
	Min	22648	96064	16874	361428	17285	36212
Group means	T-statistic	-1.618	-1.0969	-0.5387	3.3848**	2.5087**	3.8542***

**p-value < 0.05; **p-value < 0.01; ***p-value < 0.001; N/S – not statistically significant; Min, Max and SD mean minimum, maximum and standard deviation respectively.*

Table 2: Tests of returns to scale

$H_0 : \psi$ is CRS	Significance level	Mean of ratios	Ratio of means	Mean of ratios minus 1	Conclusion
Test statistic		0.9442	0.9477	-0.0142	Fail to reject CRS
Critical Value	5%	0.6610	0.7294	-0.0369	Fail to reject CRS
	1%	0.5430	0.5257	-0.0534	Fail to reject CRS

In line with Ohene-Asare, Asare, and Turkson (2019), non-life insurers were shown to have higher levels of operating expenses and equity capital than life insurers. However, these findings were not consistent with the phenomenal growth observed in life businesses compared to non-life businesses (Alhassan et al., 2015).
Unlike previous efficiency and dynamic productivity studies that failed to statistically test the nature of returns to scale (Lozano & Soltani, 2020; Ohene-Asare et al., 2019), the return to scale technology of the Ghanaian insurance industry is tested following Ohene-Asare et al. (2017) and Tortosa-Ausina et al. (2012) to avoid biased and misleading conclusions on the efficiency scores (Dyson et al., 2001; Simar & Wilson, 2002). The three different RTS tests (mean of ratios, ratio of means, and mean of ratios minus 1) are performed to determine the appropriate RTS technology for the Ghanaian insurance industry. The null hypothesis of all three tests shows the production technology to be globally constant return to scale (CRS) (see Table 2).

5. Findings and discussion

5.1 Claims as undesirable output

To assess the effect of an undesirable output on the MEA efficiency of insurers, claims is used as a desirable and undesirable output in the efficiency analysis. As MEA efficiency scores are measured relative to a common pooled frontier, a combined meta-analysis of all the observations from all years (2008–2019) is measured against a common meta-frontier and then classified across time, firms, and groups for feasible and practical comparisons. Table 3a and 3b presents the number of times insurers were efficient on claims and the corresponding efficiency percentage for the study period.
From Table 3a and 3b, Enterprise Life (Enter L) scored the highest (99%) on claim efficiency, whereas MetLife scored the second highest (98%) when claims were considered as an undesirable output. However, these efficiency scores changed when claims were considered as a desirable output (MetLife - 100%, Enterprise Life – 87%). Likewise, the average insurer recorded lower efficiency scores when claims were considered desirable rather than undesirable. This conclusion implies that had we used claims as a desirable output, misleading results could have emerged. Another potentially practical justification for considering claims as an undesirable output emanates from the rankings of the efficiency scores. Specifically, the rankings of 21 out of 30 insurers changed between the two models (desirable and undesirable claims). Star Life (Star L), for instance, was ranked 5th when claims were considered as an undesirable output but ranked 2nd when claims were considered as a desirable output. Glico Life (Glico L) ranked 9th (least ranked) when claims were undesirable and 6th when claims were desirable. These findings suggest that the claims efficiency could be underestimated or overestimated depending on whether it was considered desirable or undesirable. Comparing desirable claims efficiency with undesirable claims efficiency revealed that insurers were

88% efficient under undesirable claims efficiency but 66% efficient under desirable claims efficiency (using the median efficiency). To test for the significant difference in the ranks rather than averages of efficiency between undesirable claims efficiency and desirable claims efficiency, the non-parametric Wilcoxon signed-rank test was used and corroborated with the dependent t-test (parametric test). The p-value (0.00) of the Wilcoxon signed-rank test statistic (W = 45230) confirmed a significant difference between the rankings of desirable and undesirable claims efficiency estimates at the 0.1% level of significance.

With the confirmed significant difference between the rankings of the two efficiencies, insurance efficiency is proven to differ when claims is treated as a desired or undesired output. The violin plot is used in Figure 1 to illustrate the kernel density graphs or box plots because it presents a five-point summary of the claim efficiency estimates in addition to the distribution of the efficiency estimates (Färe et al., 2015; Liu et al., 2021). Besides the density traces of the violin plot, it provides new information on the shape of the distribution for the claims efficiencies (Hintze and Nelson 1998). In addition, the violin plot can portray the presence of clusters in the nonparametric data, and the densities can showcase the peaks, bumps, and valleys in the distribution. It combines the merits of the box plots with density traces in one diagram by making the width of the box proportional to the estimated density (Färe et al., 2015). With the confirmed significant difference between the rankings of the two efficiencies, insurance efficiency is proven to differ when claims is treated as a desired or undesired output. The violin plot is used in Figure 1 to illustrate the kernel density graphs or box plots because it presents a five-point summary of the claim efficiency estimates in addition to the distribution of the efficiency estimates (Färe et al., 2015; Liu et al., 2021).

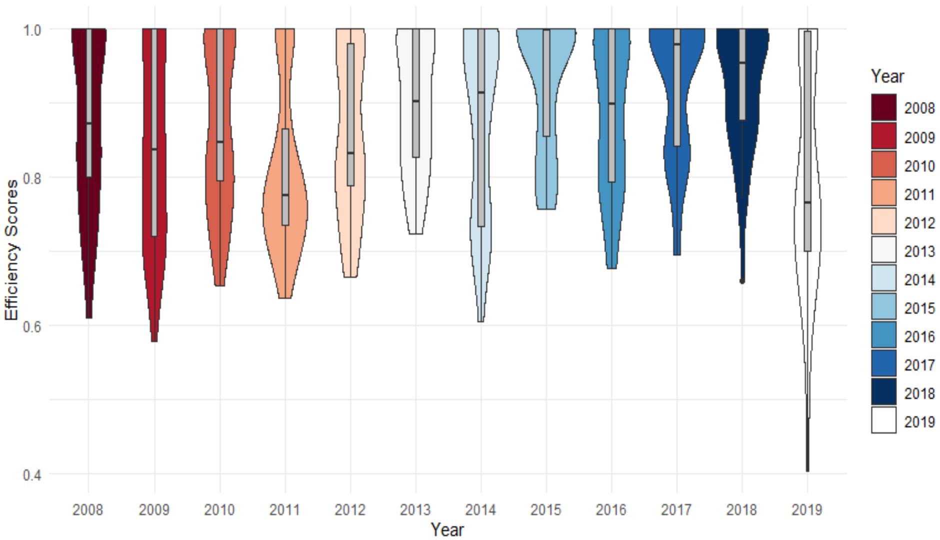

Figure 1: Claims efficiency for insurers across the years

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5.2 Variable-specific efficiencies

To assess the variable-specific efficiencies, the vectors of variable-specific efficiencies (c.f. eqns. 7-10) for each observation are considered. Figure 2 presents the average variable-specific and comprehensive efficiencies across the insurers as measured against the pooled frontier. First, Figure 2 reveals that larger parts of insurers' variables are performing MEA efficiently on the combined variables in the insurance sector, as efficiency scores are more than 50% generally. The result implies that there is less potential to cut inputs and undesirable outputs or raise desirable outputs. However, investment income inefficiency is the primary cause of comprehensive MEA inefficiency, as shown in Figure 2. It is also observed that the average aggregated or integrated MEA efficiencies and investment income efficiencies are generally lower than those of the other variable-specific efficiency scores across insurance firms. The similar pattern of lower investment income efficiencies appears to underlie the lower comprehensive efficiencies. Overall, we observe that insurers generally perform well on the variable-specific efficiency scores, with the exception of investment income, when compared to the average comprehensive MEA efficiencies.

Second, Figure 3 depicts the violin plots for the disaggregated efficiency scores. Except for the efficiency distribution of investment income, a similar spread and distributional pattern are shown for all the variables. This pattern confirms the lower average efficiencies recorded on investment income across the years. Claims are shown to have the fattest density followed by labour and equity capital. The relatively small spread on the claims' efficiency density reveals the higher efficiencies recorded by insurers. The wider spread in net premium efficiency distribution, coupled with their thin densities, reveals the relatively lower efficiencies recorded by some insurers. Overall, insurers have demonstrated strong performance across all variables, with the exception of investment income.

Table 3a: Average claims efficiency scores (and rankings) for claims as a desirable and an undesirable output (2008 - 2019).

	Claims as an undesirable output				Claims as a desirable output			
Insurer	**Claims Efficiency**	**No. of years claims is efficient out of 12 years**	**Percentage of times efficient**	**Rank**	**Claims Efficiency**	**No. of years claims is efficient out of 12 years**	**Percentage of times efficient**	**Rank**
Activa I	0.83	1	8.30%	9th	0.37	1	8.33%	8th
CDH L	0.76	1	8.30%	9th	0.51	0	0.00%	
Donewell IC	0.84	2	16.70%	8th	0.46	1	8.33%	8th
Donewell L	0.87	5	41.70%	5th	0.75	5	41.67%	5th
Enter L	**0.99**	**10**	**83.30%**	**2nd**	**0.87**	**7**	**58.33%**	**3rd**
Enterprise IC	0.85	5	41.70%	5th	0.81	5	41.67%	5th
Equity IC	0.93	6	50.00%	4th	0.4	0	0.00%	
Ghana L	0.84	5	41.70%	5th	0.65	3	25.00%	6th
Ghana UA	0.79	1	8.30%	9th	0.61	1	8.33%	8th
GhanaUnion L	0.95	5	41.70%	5th	0.44	0	0.00%	
Glico GI	0.78	1	8.30%	9th	0.55	0	0.00%	
Glico L	**0.82**	**1**	**8.30%**	**9th**	**0.85**	**3**	**25.00%**	**6th**
Met L	**0.98**	**11**	**91.70%**	**1st**	**1**	**12**	**100.00%**	**1st**
Metropolitan IC	0.83	2	16.70%	8th	0.8	3	25.00%	6th
NSIA GC	0.86	3	25.00%	7th	0.33	0	0.00%	
Phoenix IC	0.86	0	0.00%		0.57	0	0.00%	
Phoenix L	0.87	6	50.00%	4th	0.75	6	50.00%	4th
Prime I	0.82	4	33.30%	6th	0.3	0	0.00%	
Provident IC	0.83	1	8.30%	9th	0.3	0	0.00%	
Provident L	0.91	5	41.70%	6th	0.87	5	41.67%	5th

*< 0.01; ***p-value < 0.001; Min, Max, SD means minimum, maximum and standard deviation respectively*

Table 3b: Average claims efficiency scores (and rankings) for claims as a desirable and an undesirable output (2008 - 2019).

	Claims as an undesirable output				Claims as a desirable output			
Insurer	Claims Efficiency	No. of years claims is efficient out of 12 years	Percentage of times efficient	Rank	Claims Efficiency	No. of years claims is efficient out of 12 years	Percentage of times efficient	Rank
Quality IC	**0.84**	**0**	**0.00%**		**0.42**	**0**	**0.00%**	
Quality L	**0.86**	**3**	**25.00%**	**7th**	**0.70**	**2**	**16.67%**	**7th**
Regency AI	**0.92**	**5**	**41.70%**	**5th**	**0.54**	**2**	**16.67%**	**7th**
SIC IC	**0.79**	**1**	**8.30%**	**9th**	**0.33**	**0**	**0.00%**	
SIC L	**0.90**	**8**	**66.70%**	**3rd**	**0.94**	**8**	**66.67%**	**2nd**
Star AC	**0.92**	**3**	**25.00%**	**7th**	**0.59**	**2**	**16.67%**	**7th**
Star L	0.89	5	41.70%	5th	0.95	8	66.67%	2nd
Unique IC	**0.82**	**4**	**33.30%**	**6th**	**0.51**	**2**	**16.67%**	**7th**
Vanguard AC	**0.9**	**3**	**25.00%**	**7th**	**0.80**	**3**	**25.00%**	**6th**
Vanguard I	**0.93**	**8**	**66.70%**	**3rd**	**0.83**	**8**	**66.67%**	**2nd**
Mean	0.87				0.67			
Median	0.88				0.66			
SD	0.12				0.28			
Min	0.40				0.02			
Max	1				1			
Count	360				360			
Test of means	T-test	13.351***						
	Wilcoxon test	45230***						

*< 0.01; ***p-value < 0.001; Min, Max, SD means minimum, maximum and standard deviation respectively*

To further assess the variable-specific efficiencies, all observations from every year are combined into one dataset for the pooled meta-analysis, as shown in Figure 4. We observe relatively stable variable-specific efficiency patterns for each variable (except investment income) as time progresses. Still, investment income efficiency was observed to be substantially increasing during the 2008-2019 period. However, we observe a slow decline in the variable-specific efficiencies after 2018. This finding reveals an equal level of performance on these variables across the years, except for 2018. Again, the average comprehensive MEA and investment income efficiencies are generally lower than those of the other variable-specific scores. This showed investment income inefficiency to be a strong contributor to the overall MEA inefficiency. The substantial increase in efficiency levels across the study period reveals improvements in investment income and insurer performance at large. In contrast to other variables, we observe a sharp decrease in investment income efficiency from 2017. Once again, the relationship between investment income and comprehensive efficiency is evident, following the same trends and patterns.

5.3. Life and non-life efficiencies

The pooled meta-analysis of all the study observations is considered as one dataset. The MEA efficiency scores of the life and non-life insurers are compared and presented in Figure 5. The plots show unimodality for life and bimodality for non-life insurers' integrated efficiencies. More skewness is observed in life than in non-life efficiencies. The violin plots of the efficiencies of life insurers showed fatter densities between the 50% and 70% average efficiency levels, whereas no efficiency densities were shown for non-life insurers beyond the 70% average efficiency level. This suggested that whereas a greater percentage of life insurers recorded average comprehensive efficiency above 50%, no non-life insurer recorded average comprehensive efficiency beyond 70%. Further observation reveals a bump in the violin plot of the non-life insurers between 50% and 25% average efficiency, suggesting that the majority of the non-life insurers recorded comprehensive average efficiency scores between 50% and 25%. Generally, non-life insurers performed more poorly than life insurers during the study period.

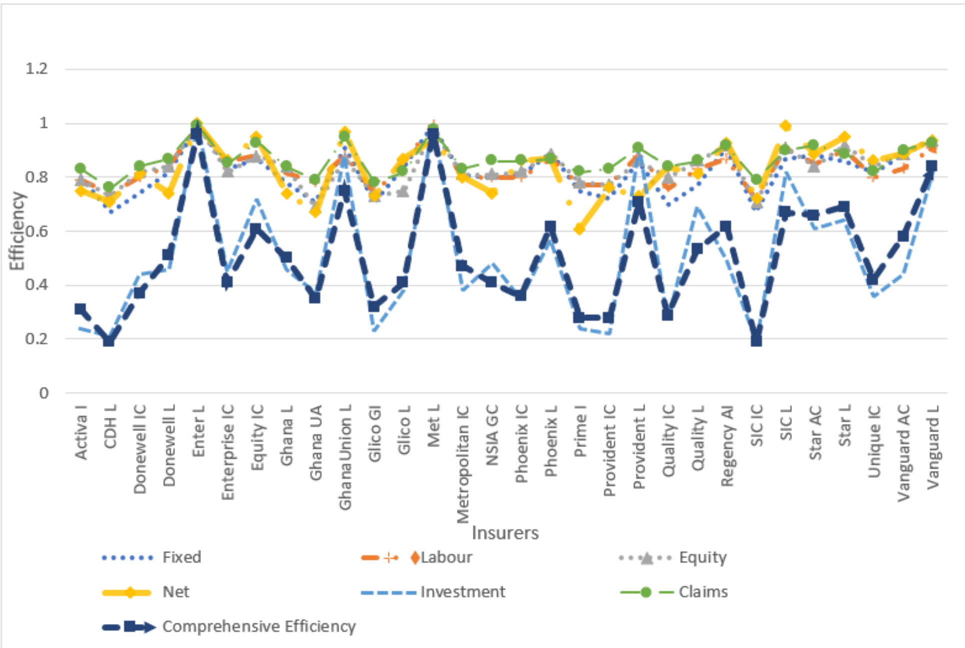
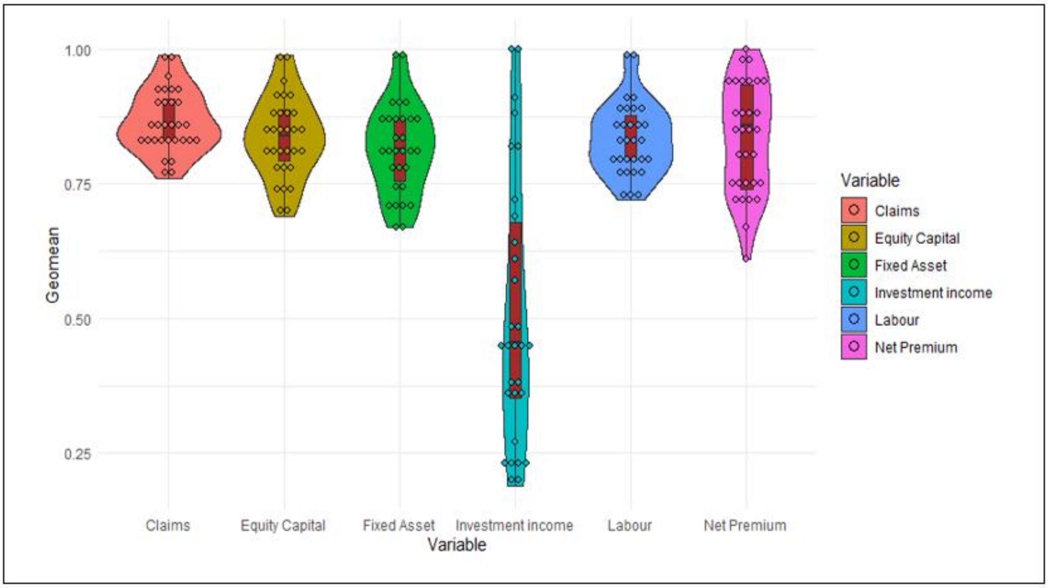


Figure 2: Average variable-specific and comprehensive efficiencies across insurers (2008 – 2019



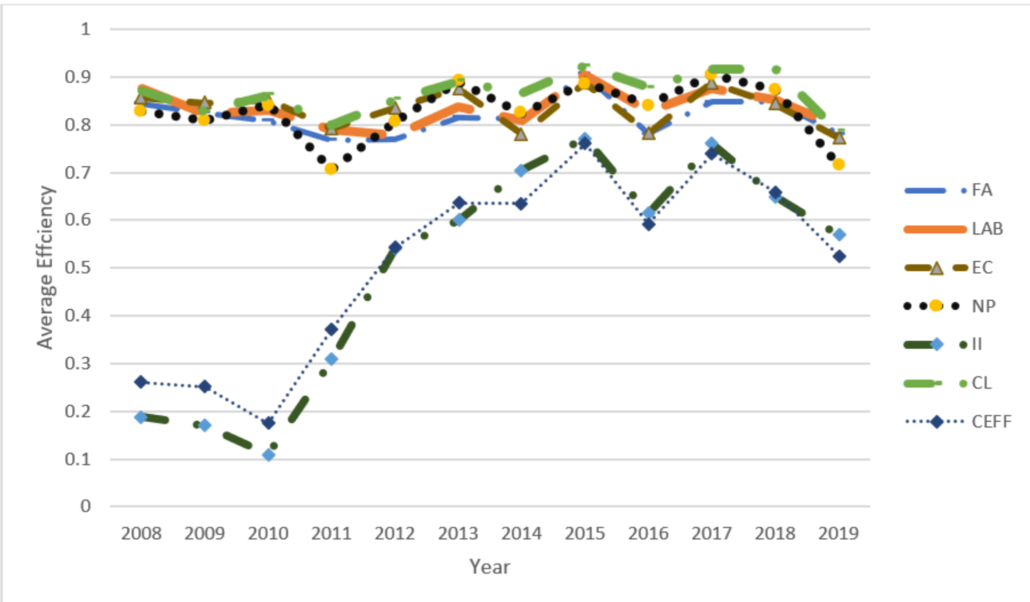


Figure 4: Average efficiencies scores over the years (2008 – 2019)

Once again, Figure 6 illustrates the violin charts showing the pooled average of disaggregated efficiency scores over 12 years, categorized and compared between life and non-life insurers. Figure 6 reveals that the life insurers exhibit a wide spread of all variable-specific efficiency scores, with the exception of net premium efficiencies. On the other hand, the variables show a relatively shorter spread for non-life insurers, with the exception of investment income efficiencies. These results suggest that the performance levels among life insurers vary widely (0.20, 1), while non-life insurers exhibit a relatively narrower range (0.20, 0.95). The non-life insurers exhibit relatively thick variable-specific efficiency distributions. Except for investment income, the bumps in the variable-specific efficiencies of the non-life insurers are shown to be around lower levels of efficiency, signifying lower levels of efficiency scores. However, the life insurers' variable-specific efficiencies showed bumps around higher efficiency levels. Overall, the life insurers outperformed non-life insurers on all variables.

A detailed examination of the pooled average variable-specific efficiency differences between life and non-life insurers for each of the input and output variables is illustrated in Figure 6 to examine the levels and patterns of efficiency differences between the life and non-life insurers. Figure 7 depicts the average efficiency scores for each insurer type in each year for each of the variables measured relative to the meta-frontier, with the life insurers being consistently more efficient than the nonlife insurers on investment income, fixed assets, equity capital, and labour, with no clear difference between them on claims and net premium during the study period. Based on the patterns, life insurers outperformed non-life insurers in fixed assets, labour, equity capital, and investment income.

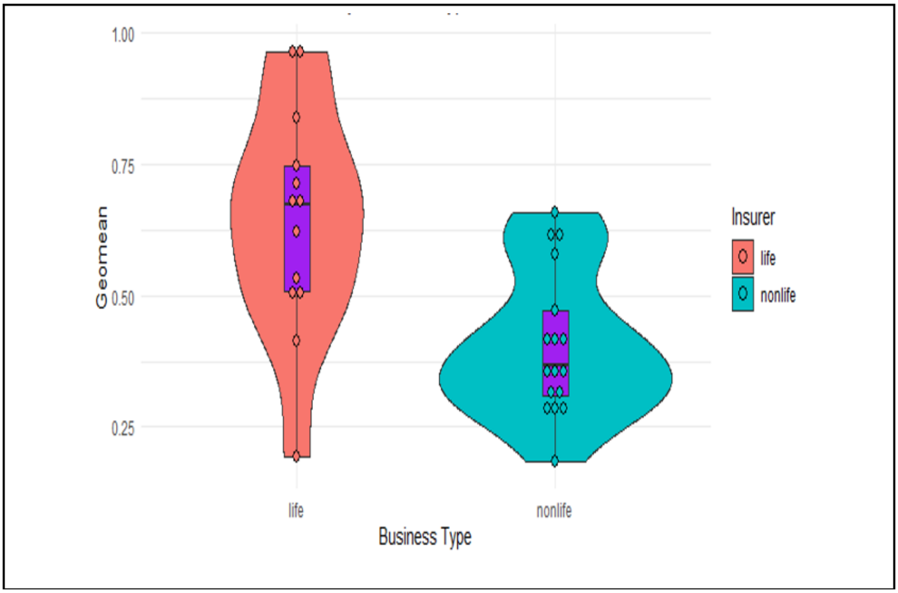


Figure 5: Distribution of average efficiency by business types (2008 -2019)

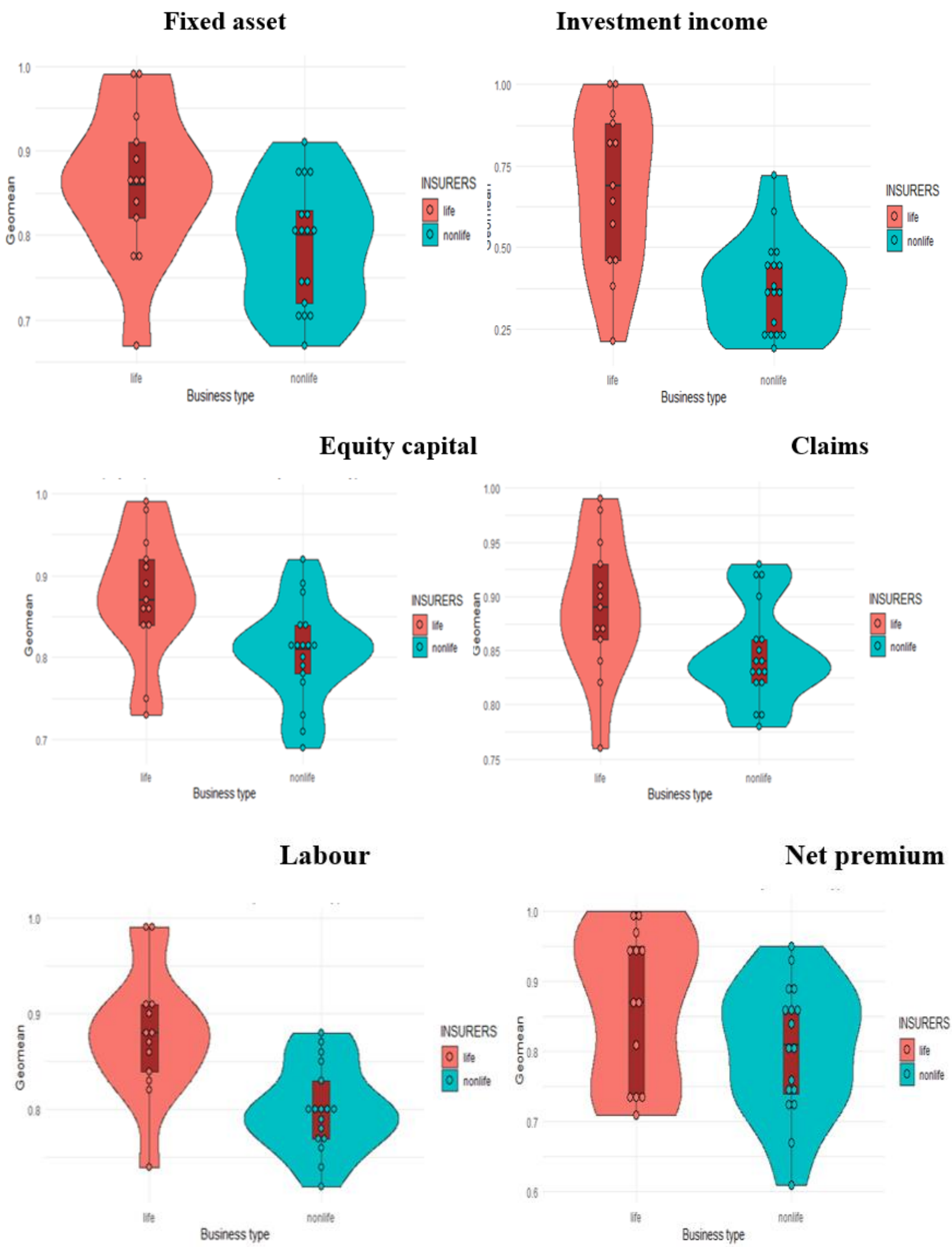


Figure 6: Average efficiency scores for each insurer type

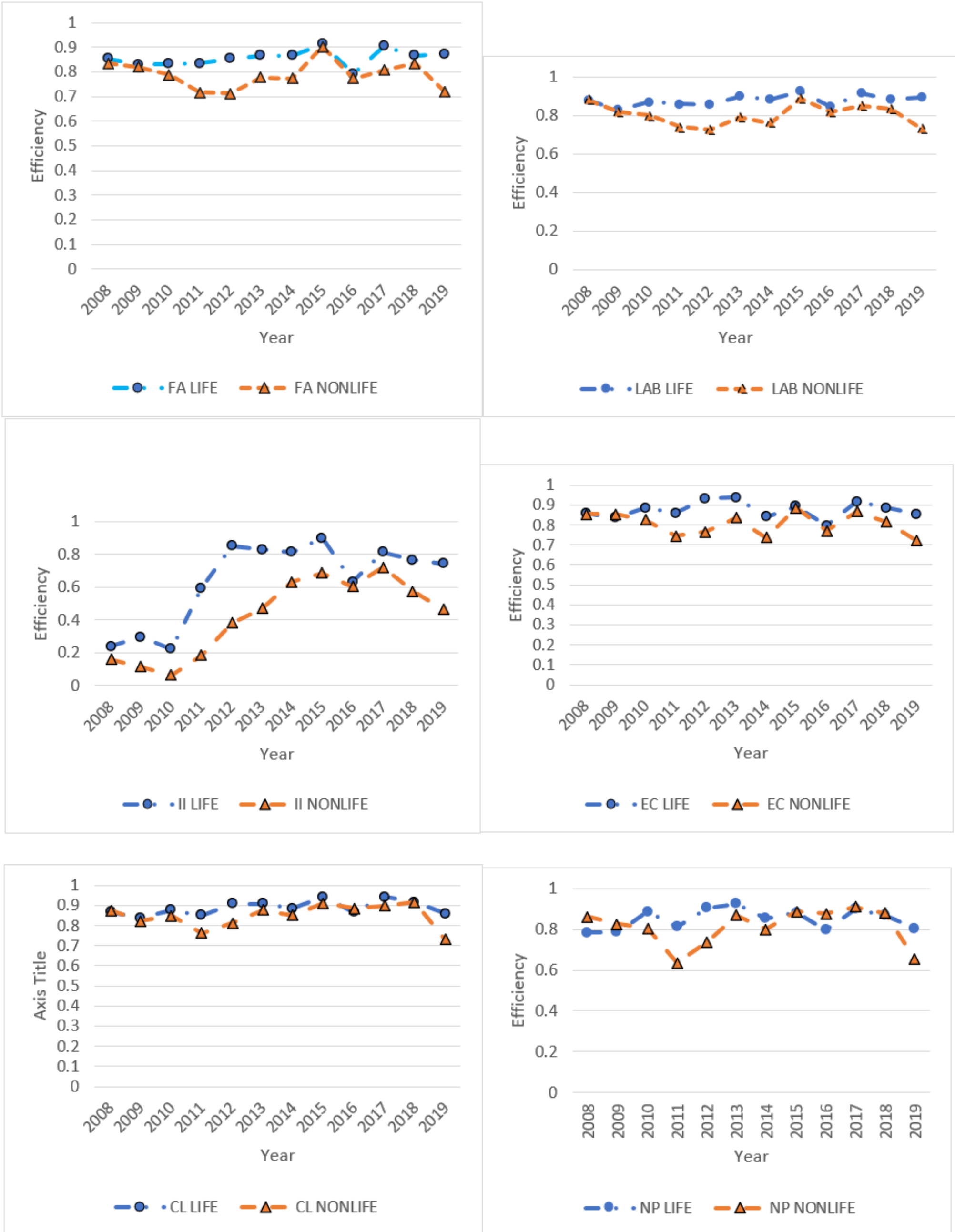


Figure 7: Variable-specific efficiencies of life and non-life insurers

5.4 Determinants of MEA efficiency

In line with Chowdhury and Zelenyuk (2016), the Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) of the three models were estimated to identify the simplest parsimonious model for the study. Based on their results (see Table 5a and 5b, model 8 is chosen as the appropriate regression model for the study.

After dropping the insignificant variables, all the significant variables remained significant in all the models. First, the lag of the aggregate efficiency scores has a significantly positive impact on aggregate efficiency. This signifies that an insurer's previous year's overall efficiency score positively impacts its current overall performance at a 0.1% significance level. This finding is consistent with Sultana and Rahman (2020), who identified a positive relationship between the cost efficiency of banks in Bangladesh and its lag. Second, the Boone Indicator (BI) significantly impacted the level of competition among insurers.

Size, solvency, ROA, type of insurer, and underwriting risk were all observed to have an insignificant impact on the comprehensive efficiency of insurers. This suggests that changes in these exogenous variables do not affect the performance of Ghanaian insurers. These findings contradict Ohene-Asare et al. (2019), Ansah-Adu et al. (2012), and Alhassan et al. (2015). However, it is consistent with Ansah-Adu et al. (2012) on the impact of the type of insurer.

Table 5a: Total sample regression results

Dependent Variable: Eff	**Pooled OLS**	**Fixed Effect**	**Randon Effect**	**RE-HAC**	**RE Beck Katz-PCSE**	**RE Driscoll-SCC**	**Two steps System GMM**			**Expected signs**
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	**(8)**	(9)	
Lag (Eff)							0.125***	**0.3527*** **	0.189***	
							(0.032)	**(0.117)**	(0.041)	
Comp	0.183***	0.180***	0.181***	0.181***	0.181***	0.181***	0.109***	**0.473***	0.101***	+
	(0.038)	(0.034)	(0.034)	(0.053)	(0.035)	(0.027)	(0.018)	**(0.206)**	(0.017)	
Lev	0.005	0.005	0.005	0.005	0.005	0.005		**-**	0.000	+
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.017)		**-**	(0.000)	
Size	-0.01	-0.013	-0.012	-0.12	-0.012	-0.012	-0.007	**-0.025**	-0.001	±
	(0.012)	(0.012)	(-0.012)	(0.009)	(0.013)	(0.013)	(0.008)	**(0.015)**	(0.008)	
Solv	0.013	0.012	0.012	0.012	0.012	0.012	-0.001	**-0.002**	-0.0107	±
	(0.007)	(0.008)	(0.007)	(0.007)	(0.09)	(0.012)	(0.008)	**(0.010)**	(0.009)	
ROA	-0.085	-0.077	-0.079	-0.079	-0.079	-0.079	-0.011	**0.001**	-	+
	(0.098)	(0.095)	(0.094)	(0.120)	(0.130)	(0.218)	(0.061)	**(0.006)**	-	
TOIlife	0.784***	-	-	-	-	-	0.005*	**0.556**	0.003	±
	(0.217)	-	-	-	-	-	(0.002)	**(0.289)**	(0.002)	
TOInon-life	0.574**	-	0.212***	-0.212***	-0.212***	-0.212***		**-**	-	
	(0.215)	-	(0.054)	(0.0480)	(0.063)	(0.049)		**-**	-	
Urisk	-0.126**	-0.135***	-0.132***	-0.132	-0.132*	-0.132	-0.005	**-0.114**	-0.021	±
	(0.04)	(0.04)	(0.039)	(0.091)	(0.053)	(0.181)	(0.027)	**(0.931)**	(0.020)	
Intercept			0.821***	0.821***	0.821***	0.821***		**-**	-	
			(0.211)	(0.167)	(2.0628)	(0.185)		**-**	-	

Table 5a: Total sample regression results

Diagnostic Tests	POLS (1)	Fixed Effect (2)	Random Effect (3)	RE-HAC (4)	RE-PCSE (5)	RE SCC (6)	Two step System GMM (7)		
R-squared	0.168	0.112	0.133						
F-Statistic	193.322**	6.796***	54.093***						
Chow test for poolability	0.032(1.33)								
DWH Test (RE verse FE)			0.9807 (54.109)						
Breusch-Godfrey test for serial correlation			0.00 (46.714)						
Breusch-Pagan test for cross-sectional dependence (RE)			0.00 (730.5)						
Pesaran CD test for cross-sectional dependence (RE)			0.00 (6.984)						
AR(1)							0.0656	**0.1471**	0.4182
AR(2)							0.0646	**0.1471**	0.4182
J Hansen							0.0613	**0.9586**	0.138
Wald test							0.000	**0.00**	0.00
No. of insurers	30	30	30						
Observations	360	360	360				360	**360**	360
Number of instrument							43	**47**	49
AIC							173	**171.7386**	171.8821
BIC							208.084	**202.8274**	202.971

*Note: Robust Standard errors in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.*

6. Conclusion

This study aimed to analyze the input/output insurance efficiency of Ghanaian life and non-life insurers. The study mathematically modeled claims as an undesirable output using the non-radial non-oriented multi-directional efficiency (MEA) of Bogetoft and Hougaard (199) and Asmild et al. (2003). We selected benchmarks such that the non-radial adjustments to the inputs and outputs correspond to the possible improvements identified by considering the individual improvement potential in the variables. Using a panel data set of 30 life and non-life insurers from 2008 to 2019, we assessed the aggregated and disaggregated efficiency levels.

The findings of the study have brought to the fore important issues that require ample consideration in insurance efficiency assessment. First, insurance efficiency is proven to differ when claims is treated as a desired or undesired output. Hence, the appropriate definition for claims must be used in insurance efficiency estimation to avoid misleading efficiency scores. Second, the sole use of the comprehensive efficiency of insurers does not provide accurate information on the utilization and generation of the input and output variables, respectively. Third, Ghanaian life insurers are more efficient than Ghanaian non-life insurers, they outperform non-life insurers on the utilization of inputs and the generation of investment income. Finally, the level of competition in the insurance industry has the highest impact on the performance of Ghanaian insurers, followed by the previous year's performance of insurers. However, size, solvency, type of insurer, and underwriting risk do not have a significant impact on the efficiency of Ghanaian insurers.

The results imply that insurers in Ghana do not efficiently manage investment income, thus, investment income in both life and non-life insurance firms can be improved to substantially improve their aggregate efficiency. The findings show that claims significantly influence efficiency scores when treated as an undesirable output, highlighting the need for accurate variable definition when assessing insurance efficiency. The NIC can consider adopting efficiency models that account for the negative effect of claims on insurance efficiency estimation. Again, the high efficiency scores of life insurers compared to non-life insurers suggest that life insurers are better at managing the insurance production process and generation of investment income. These advantages could be due to their longer investment duration and more predictable cash flows than the non-life insurers.

Future research can be undertaken to assess the input/output-specific dynamic productivity change and cost efficiency of Ghanaian insurers in the presence of undesirable outputs with the novel MEA model. Additionally, future studies can evaluate how insurer variables contribute to overall efficiency, aiming to identify the specific impacts of these variables on comprehensive efficiency. Hence, NIC must enact policies to guide the selection and management of investment products in the Ghanaian insurance industry. Much attention should be paid to the amount of investment income reported by insurers in their quarterly reports; such information will help the NIC identify potential downfalls with investment income generation. Moreover, the NIC should organize investment training sessions for insurers. The NIC should obligate both non-life and life insurers to invest with well-performing financial institutions.

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